# Two-Layer Mutually Reinforced Random Walk for Improved Multi-Party Meeting Summarization

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Language Technologies Institute · Carnegie Mellon University

# Outline

- Introduction
- Approach
- Experiments
- Conclusion

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- Motivation
- Extractive Summarization

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# Motivation

- Speech Summarization
  - Spoken documents are more difficult to browse than texts
    → easy to browse, save time, easily get the key points
- Multi-Party Corpus
  - Speaker information may help summarization

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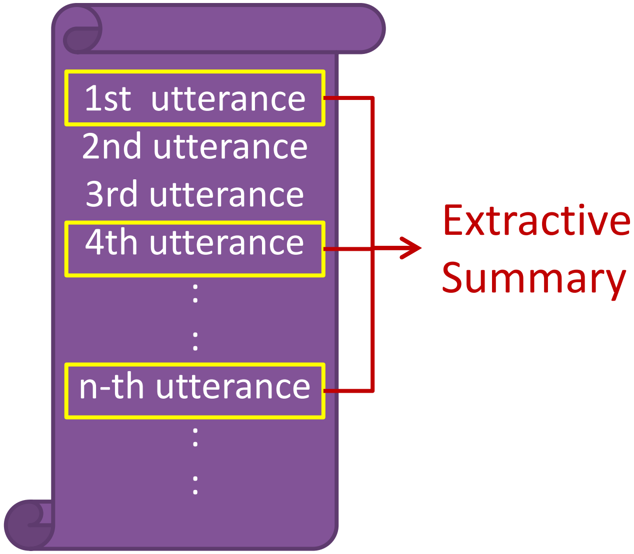
# Extractive Summarization (1/2)

- Extractive Speech Summarization
  - Select the indicative utterances in a spoken document
  - Cascade the utterances to form a summary




How to select indicative utterances?

# Extractive Summarization (2/2)

- Selection of Indicative Utterances
  - Each utterance U in a spoken document d is given an *importance score* I(U, d)
  - Select the indicative utterances based on I(U,d)
  - The number of utterances selected as summary is decided by a predefined ratio

utterance term

$$U = t_1 t_2 \ldots\ldots t_i \ldots\ldots t_n$$

$$\mathrm{I}(U, d) = \sum_{i=1}^{n} \left[ \boxed{s(t_i, d)} \cdot \cdots \cdot \right] + \cdots\cdots$$

Importance score term statistical measure (ex. TF-IDF)

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  - Within- and Between-Layer Propagation (MRRW-WBP)

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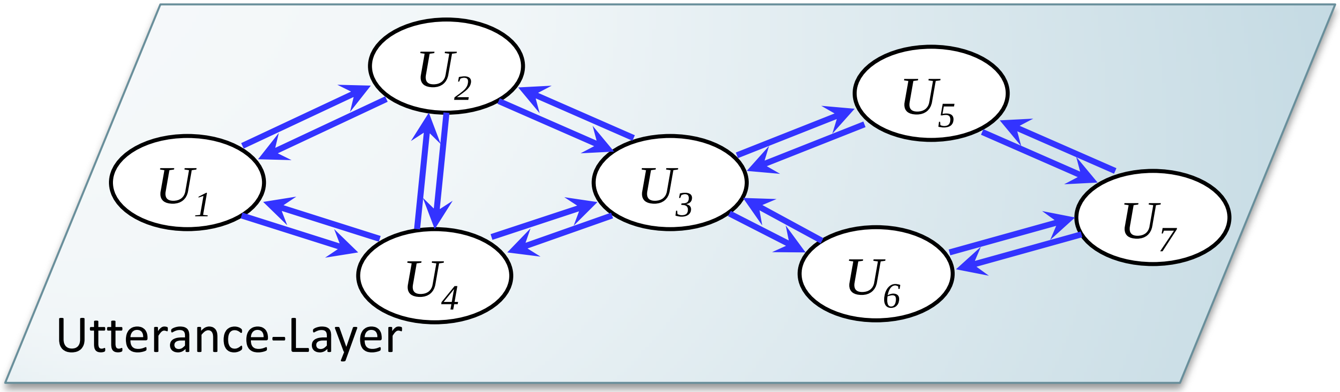
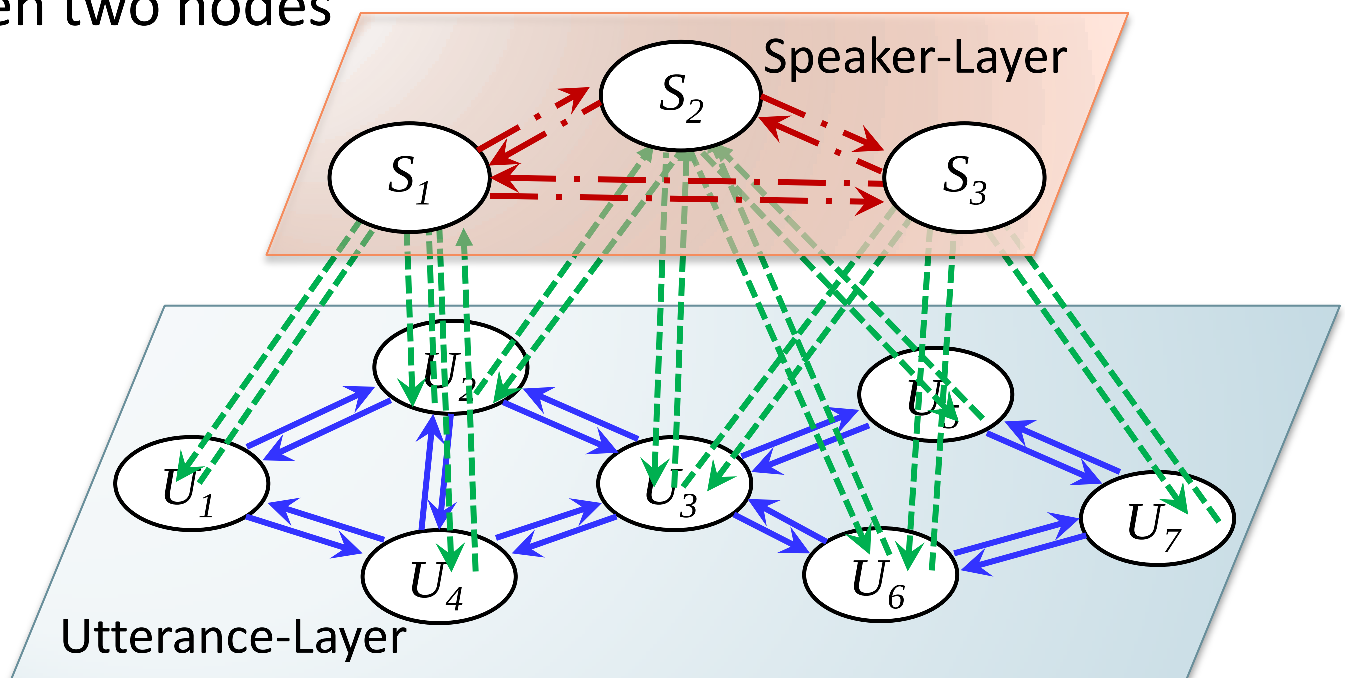
# Graph Construction (1/2)

- Utterance-Layer
  - Each node is the utterance in the meeting document
  - The edge is weighted by topical/lexical similarity between two utterances



# Graph Construction (2/2)

- Speaker-Layer
  - Each node is the speaker in the meeting document
    - Combine all utterances from the same speaker as the speaker node
  - The edge (red and green) is weighted by lexical similarity between two nodes



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# Two-Layer Mutually Reinforced Random Walk (1/3)

- Similarity Matrix
  - $L_{UU}$: utterance-to-utterance relation (topical/lexical similarity)
  - $L_{SS}$: speaker-to-speaker relation (TF-IDF cosine similarity)
  - $L_{US}$: utterance-to-speaker relation (TF-IDF cosine similarity)
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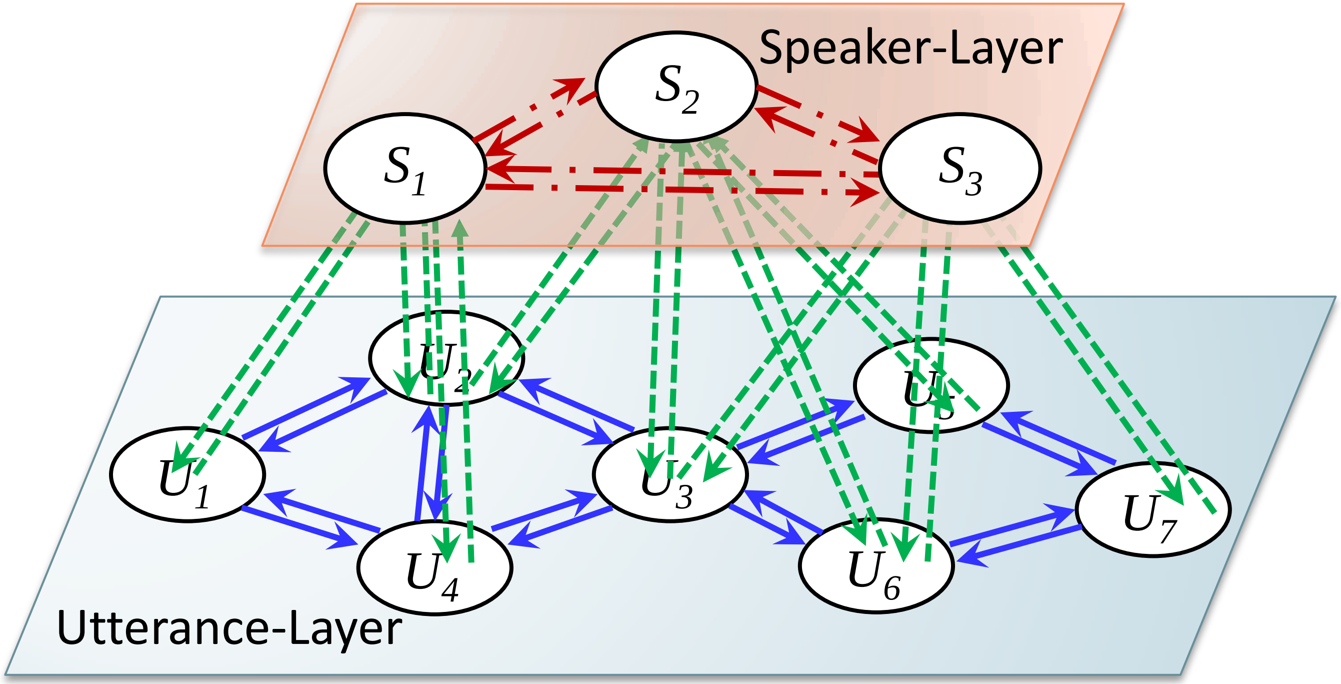

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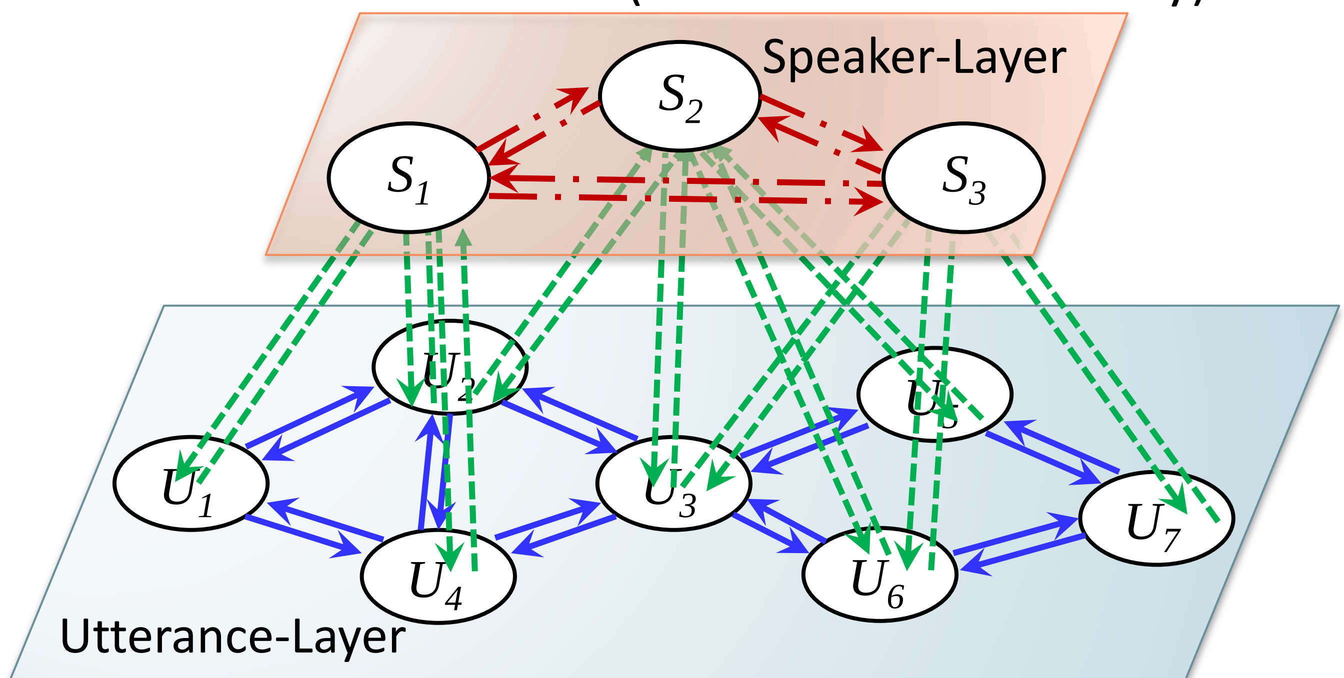
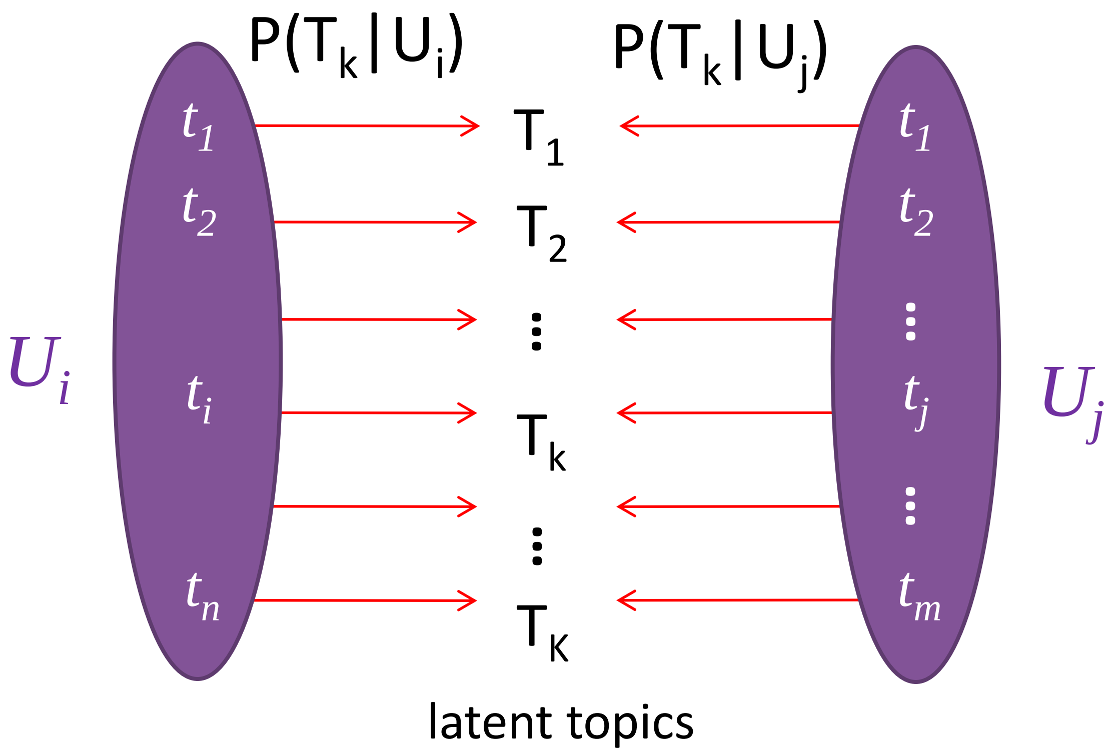


# Two-Layer Mutually Reinforced Random Walk (2/3)

- Topical similarity between utterances
  - Edge weight TopicSim($U_i$, $U_j$) (utterance $U_i$ → utterance $U_j$)




TopicSim($U_i$, $U_j$): latent topic similarities of $U_i$ to $U_j$ based on PLSA model

# Two-Layer Mutually Reinforced Random Walk (3/3)

- Lexical similarity between utterances
  - Cosine similarity between TF-IDF vectors from $U_i$ and $U_j$

LexSim($U_i$, $U_j$): evaluated by the word overlap between two utterances

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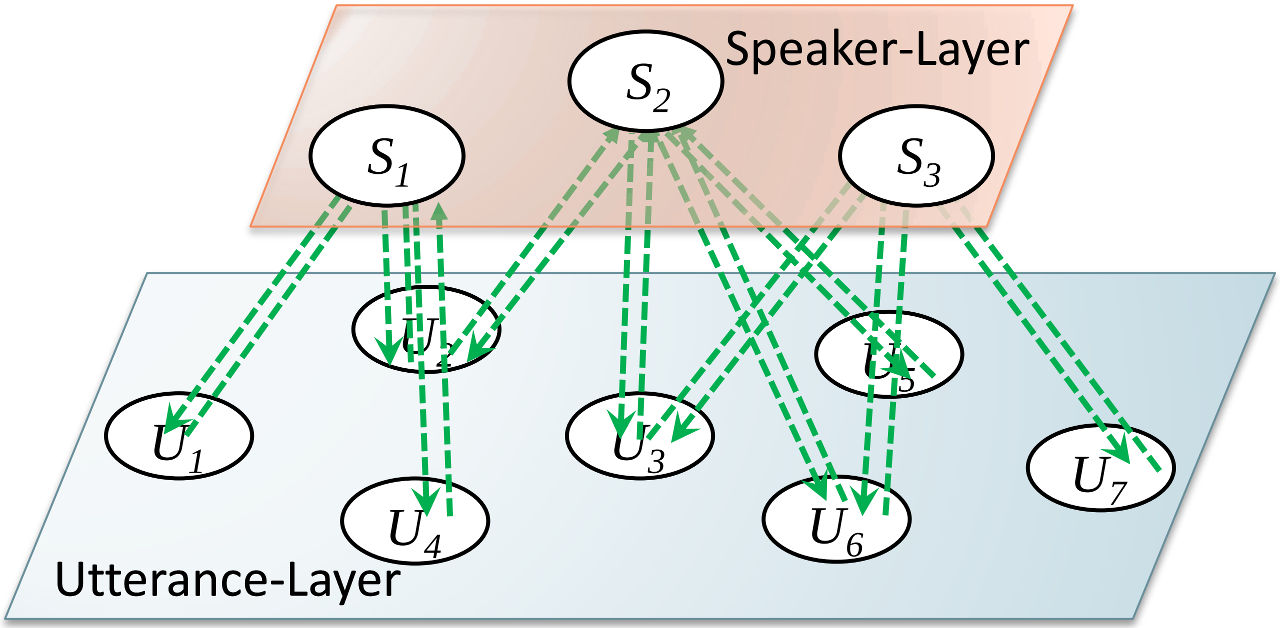
# Two-Layer MRRW-BP (Between-Layer Propagation) (1/2)

- Mathematical Formulation

utterance score at (t+1)-th iteration

$$\begin{cases} \boxed{F_U^{(t+1)}} = (1-\alpha)F_U^{(0)} + \alpha \cdot L_{US} F_S^{(t)} \\ F_S^{(t+1)} = (1-\alpha)F_S^{(0)} + \alpha \cdot L_{SU} F_U^{(t)} \end{cases}$$



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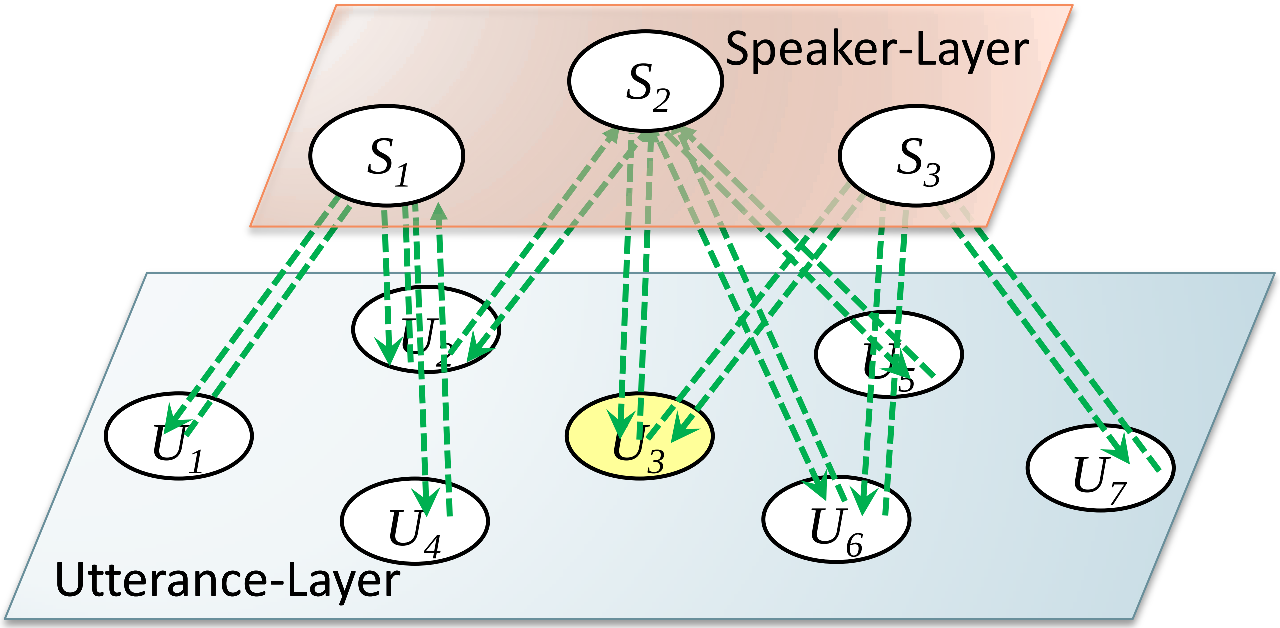

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original importance of utterance

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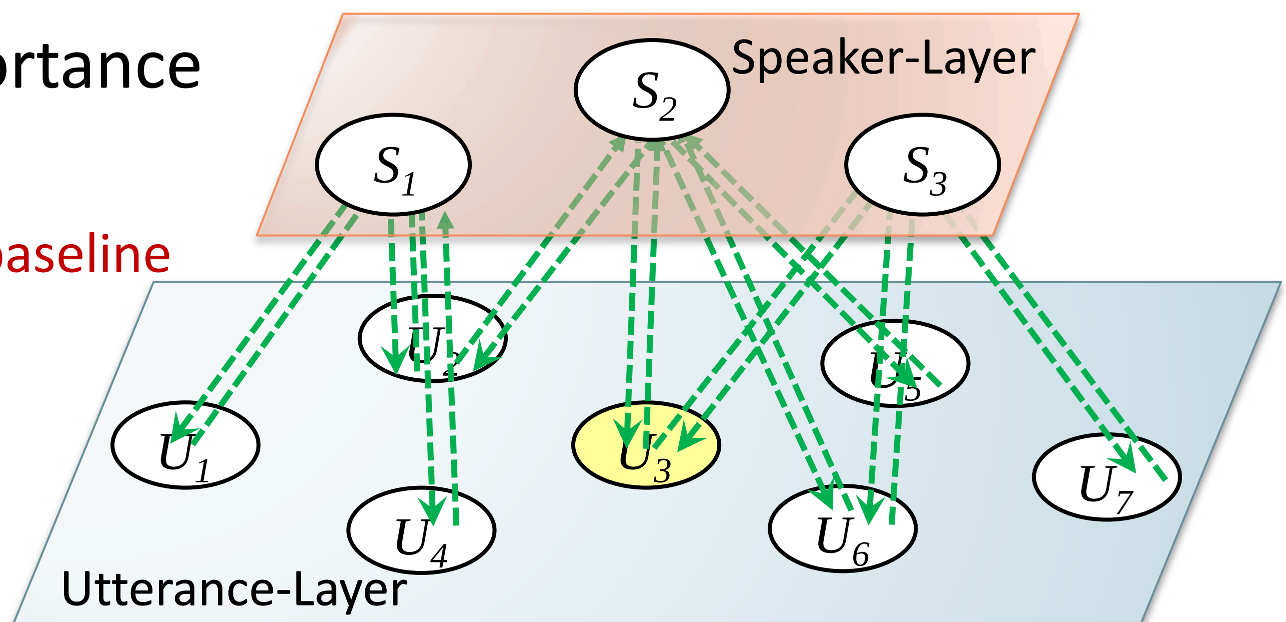
- Original importance
  - Utterance

    $I(U,d)$ → baseline



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scores propagated from speaker-layer

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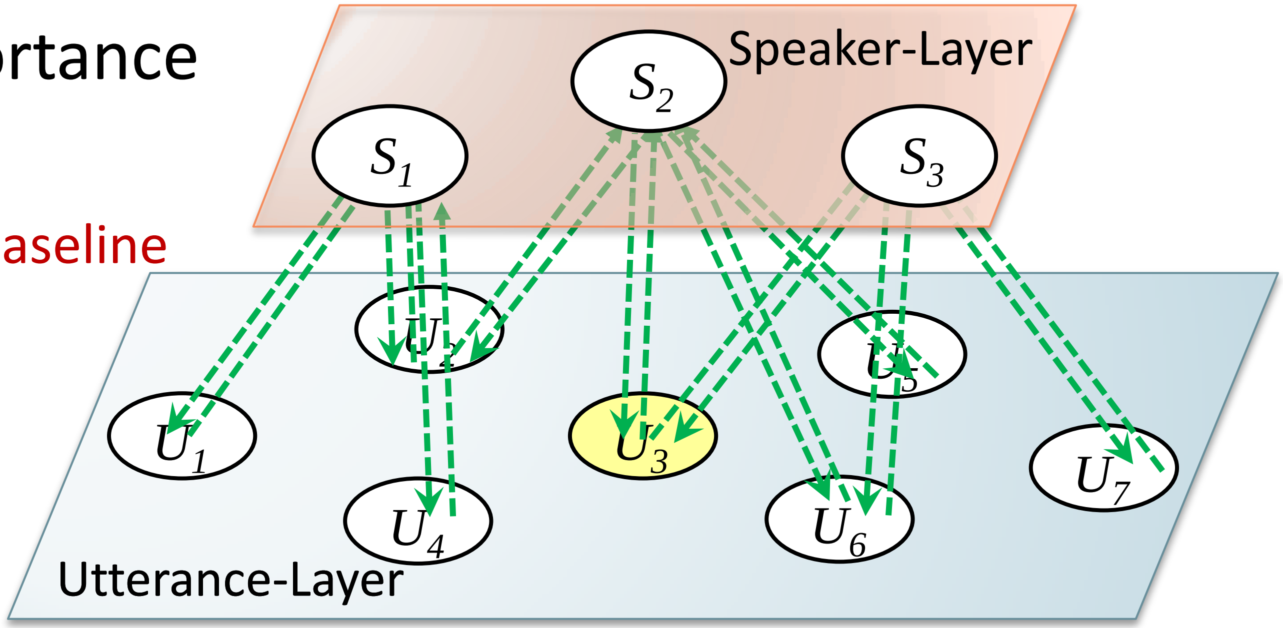

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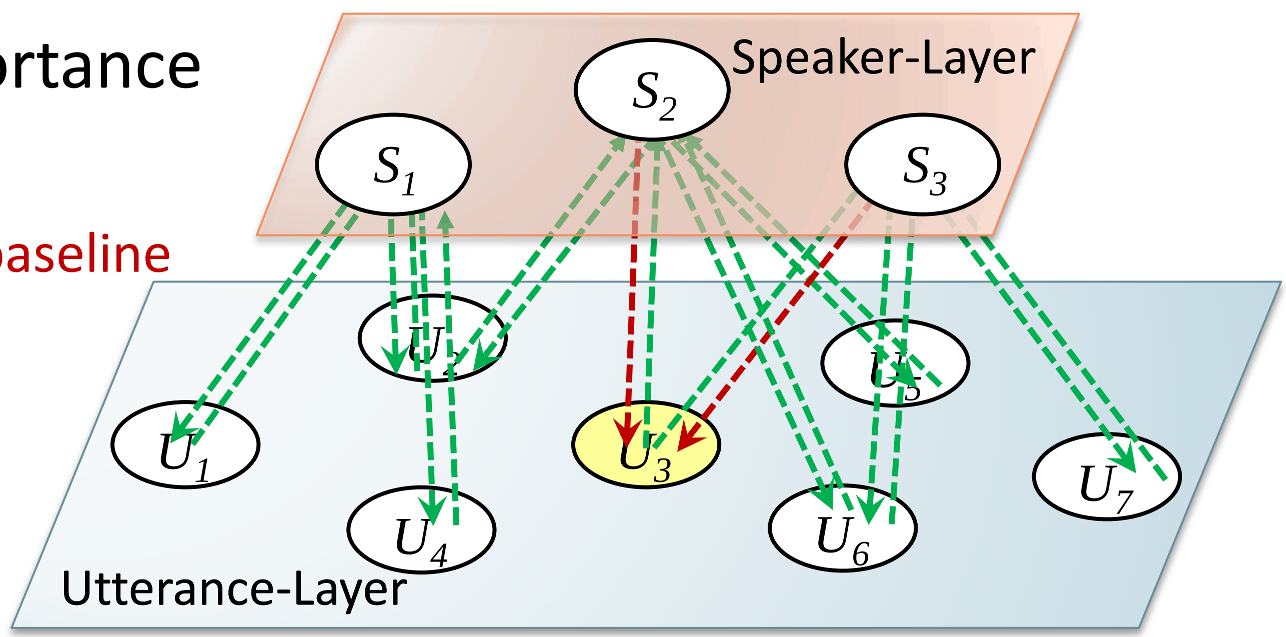

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speaker score at (t+1)-th iteration

- Original importance
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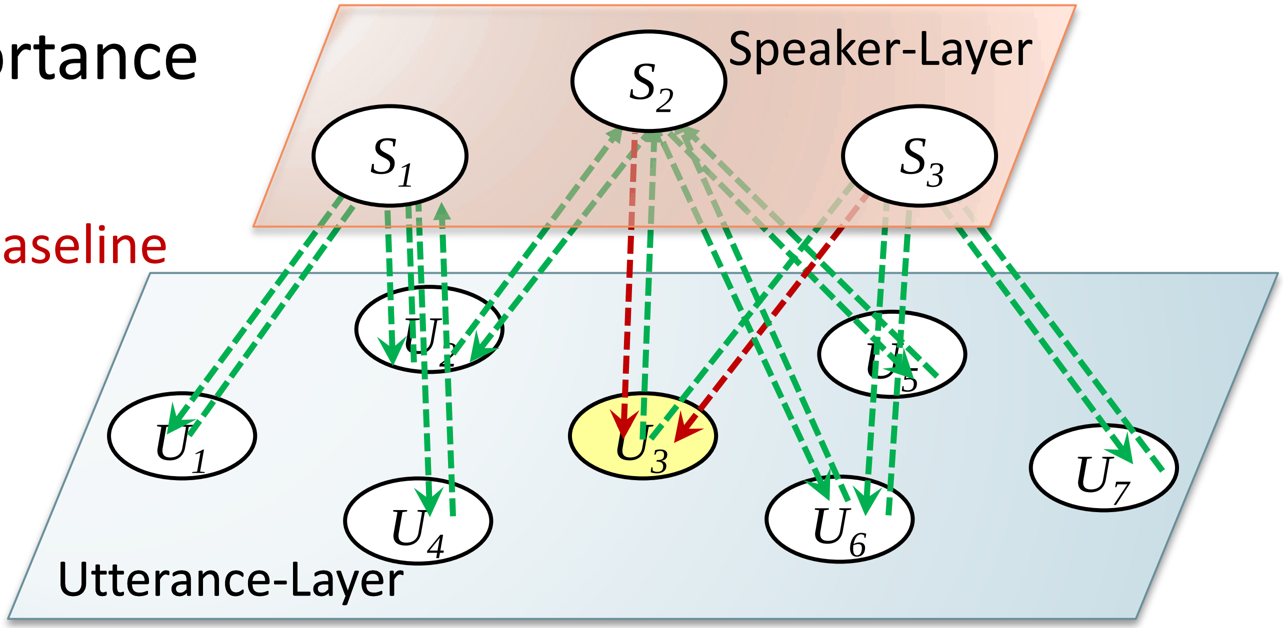

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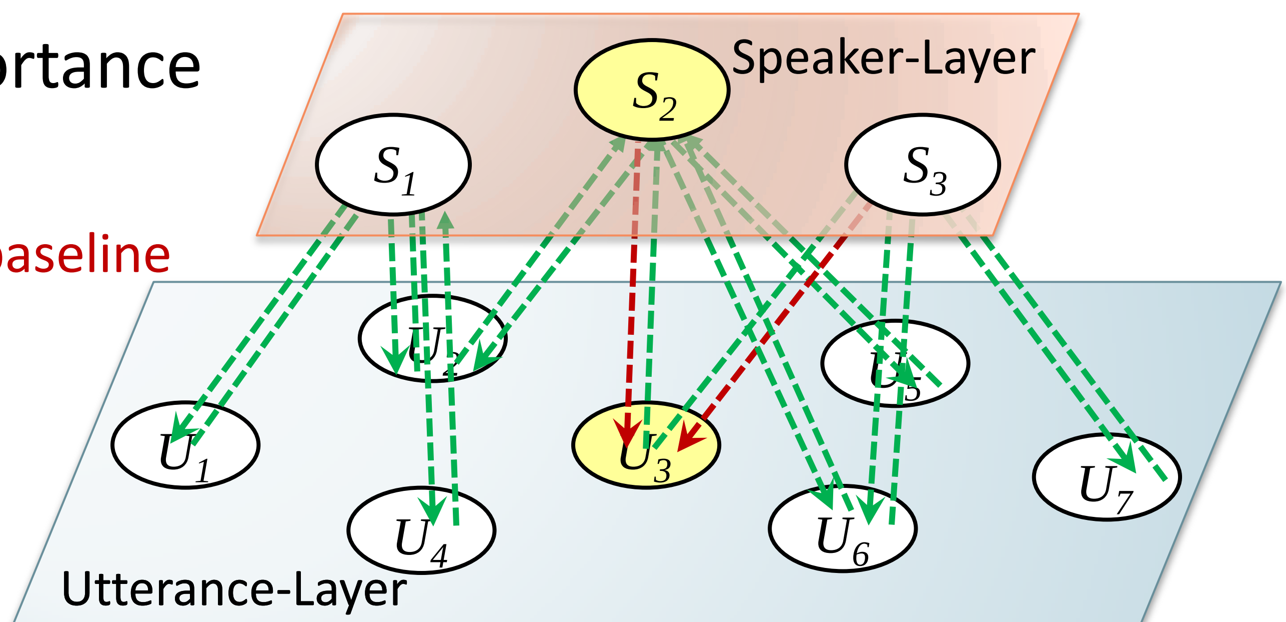

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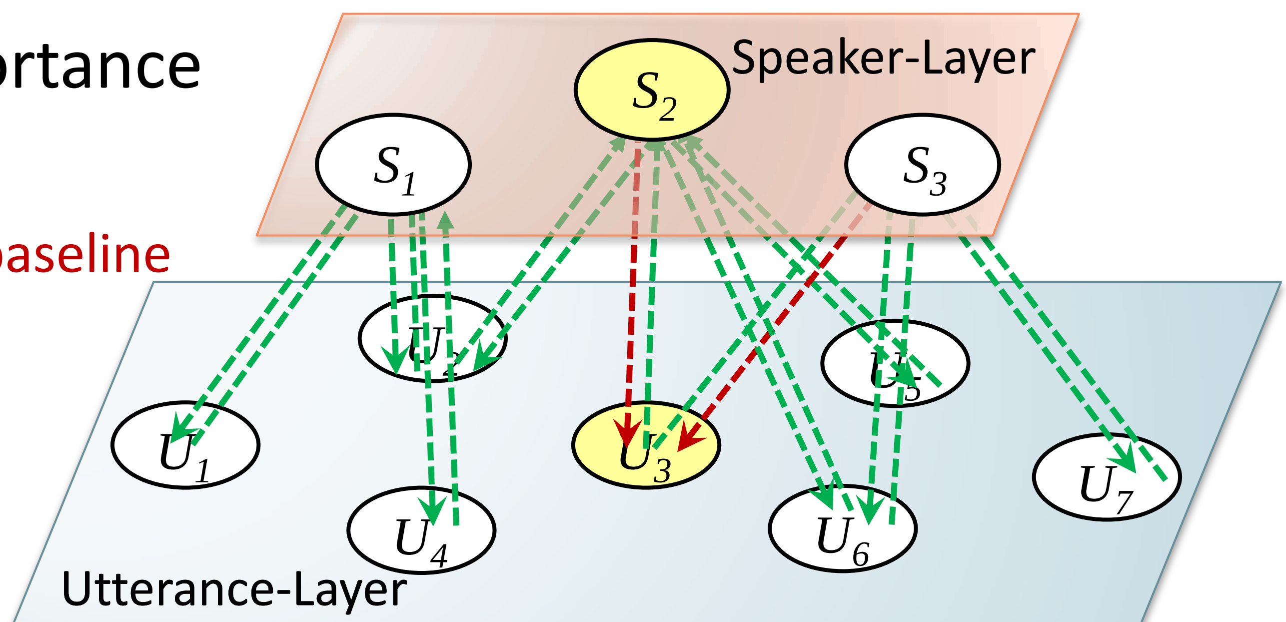
original importance of speaker

- Original importance
  - Utterance
    $I(U, d)$ → baseline
  - Speaker
    Equal weight



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scores propagated from utterance-layer

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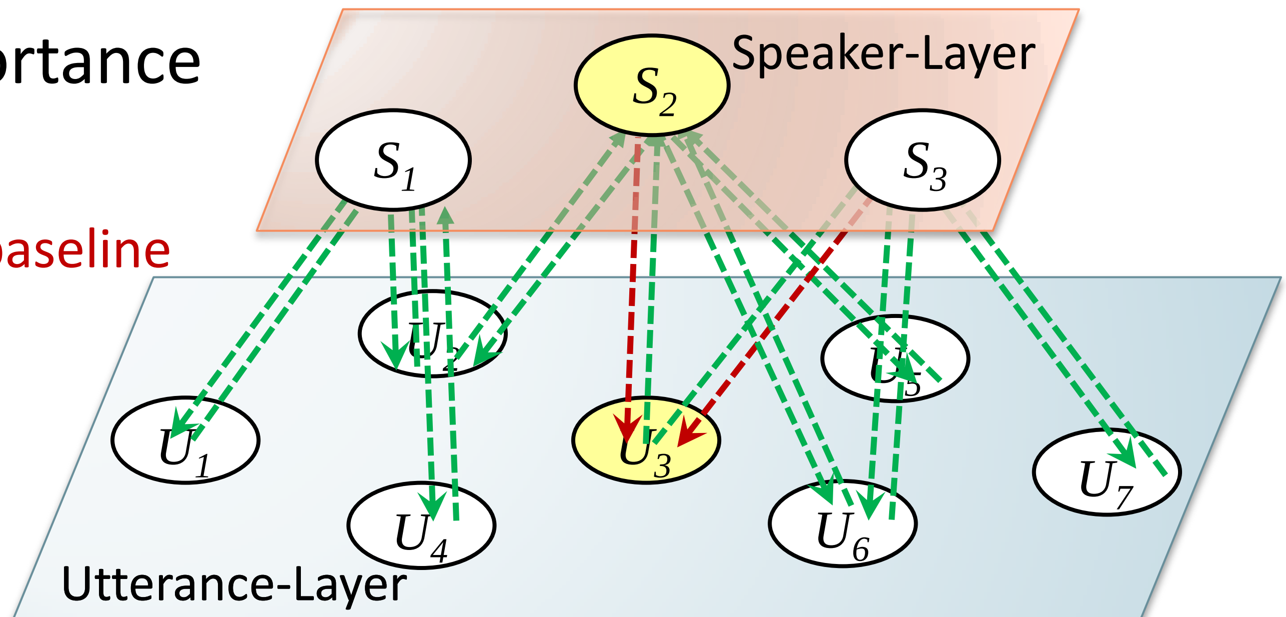

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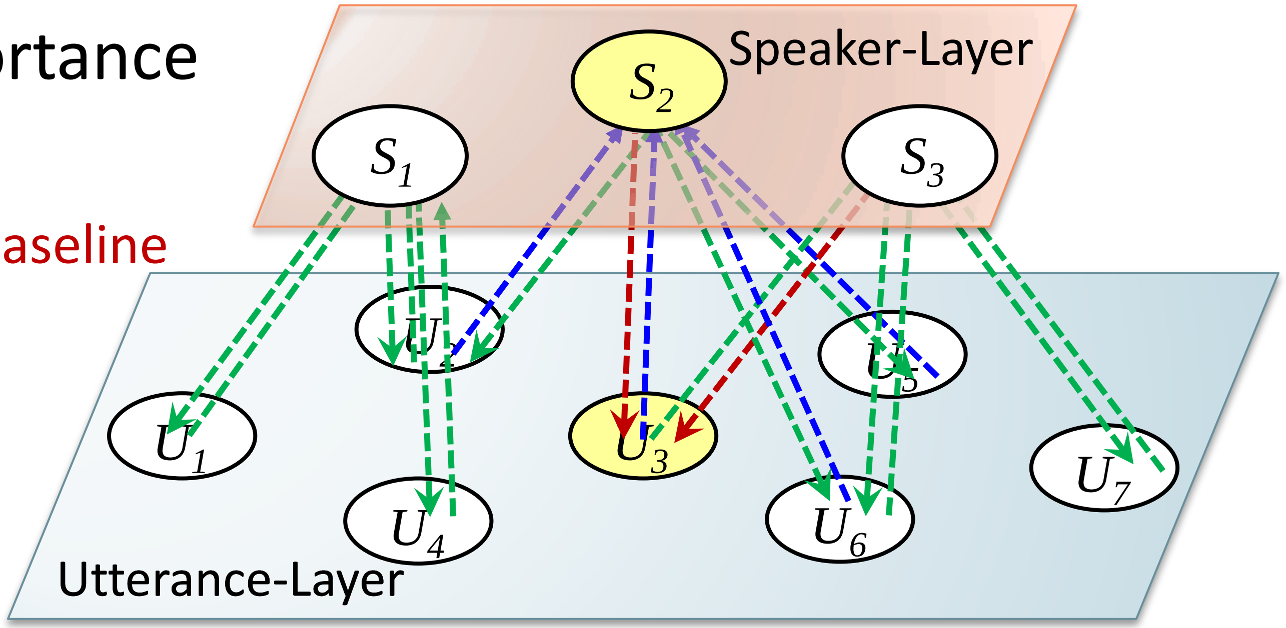

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Utterance node U can get higher score when

① Higher original importance I(U, d)

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# Two-Layer MRRW-BP (Between-Layer Propagation) (2/2)

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- Converged Solution

$$\begin{cases} F_U^* = (1-\alpha)F_U^{(0)} + \alpha \cdot L_{US} F_S^* \\ F_S^* = (1-\alpha)F_S^{(0)} + \alpha \cdot L_{SU} F_U^* \end{cases}$$

$$\begin{aligned} F_U^* &= (1-\alpha)F_U^{(0)} + \alpha \cdot L_{US}\left((1-\alpha)F_S^{(0)} + \alpha \cdot L_{SU} F_U^*\right) \\ &= \left((1-\alpha)F_U^{(0)} e^T + \alpha(1-\alpha)L_{US}F_S^{(0)}e^T + \alpha^2 L_{US}L_{SU}\right) F_U^* \\ &= M_1 F_U^* \end{aligned}$$

$F_U$* (final utterance scores) is the dominate eigenvector of $M_1$

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# Two-Layer MRRW-WBP (Within- and Between-Layer Propagation) (1/2)

- Mathematical Formulation

scores propagated from speaker-layer then propagated within utterance-layer

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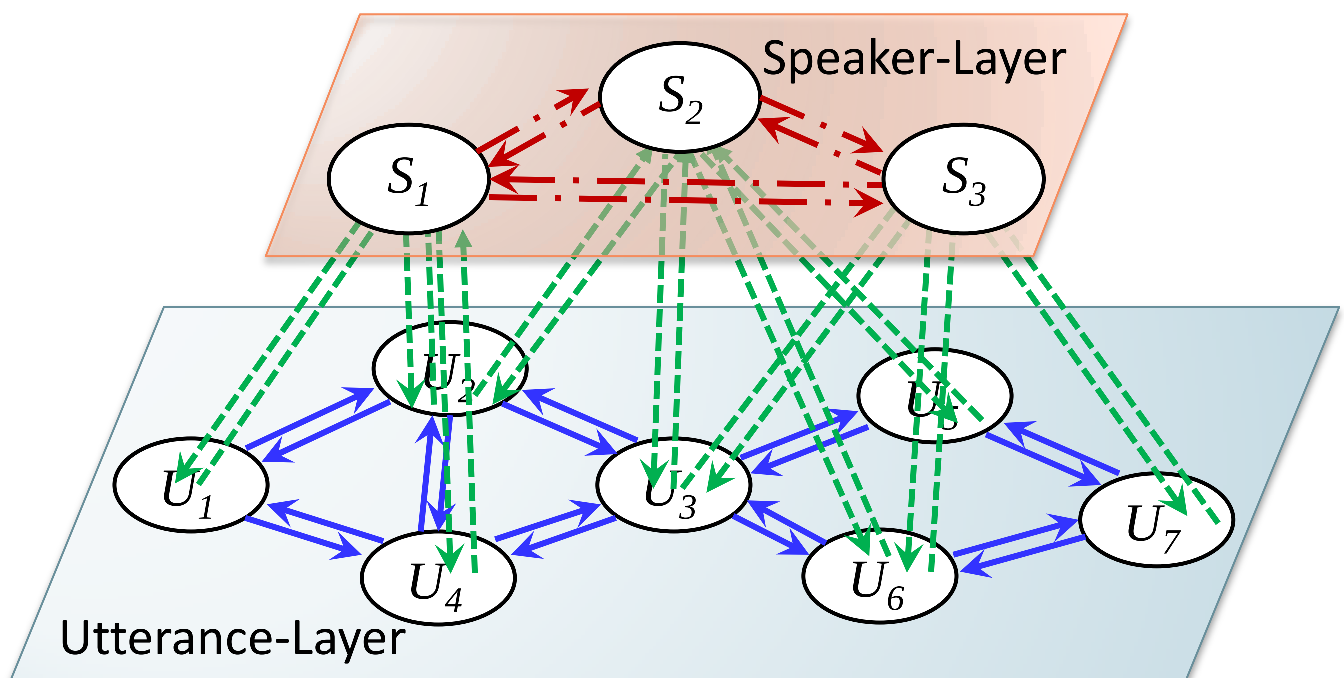

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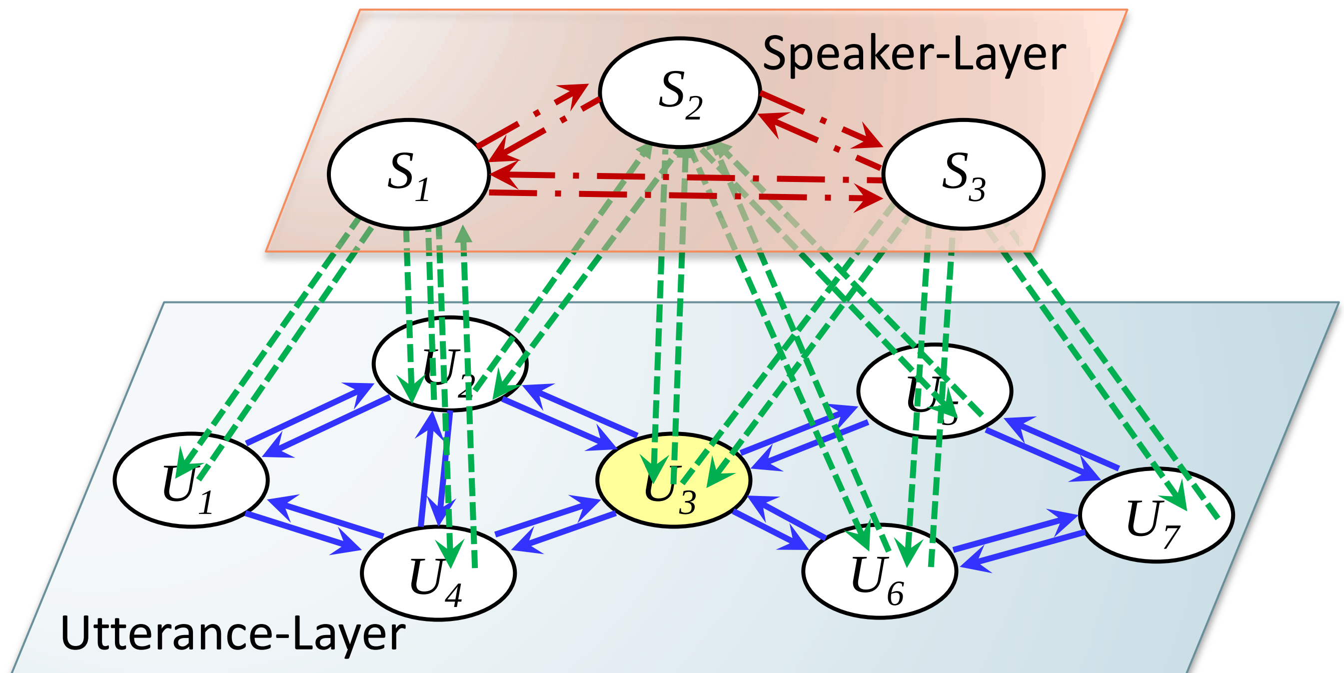

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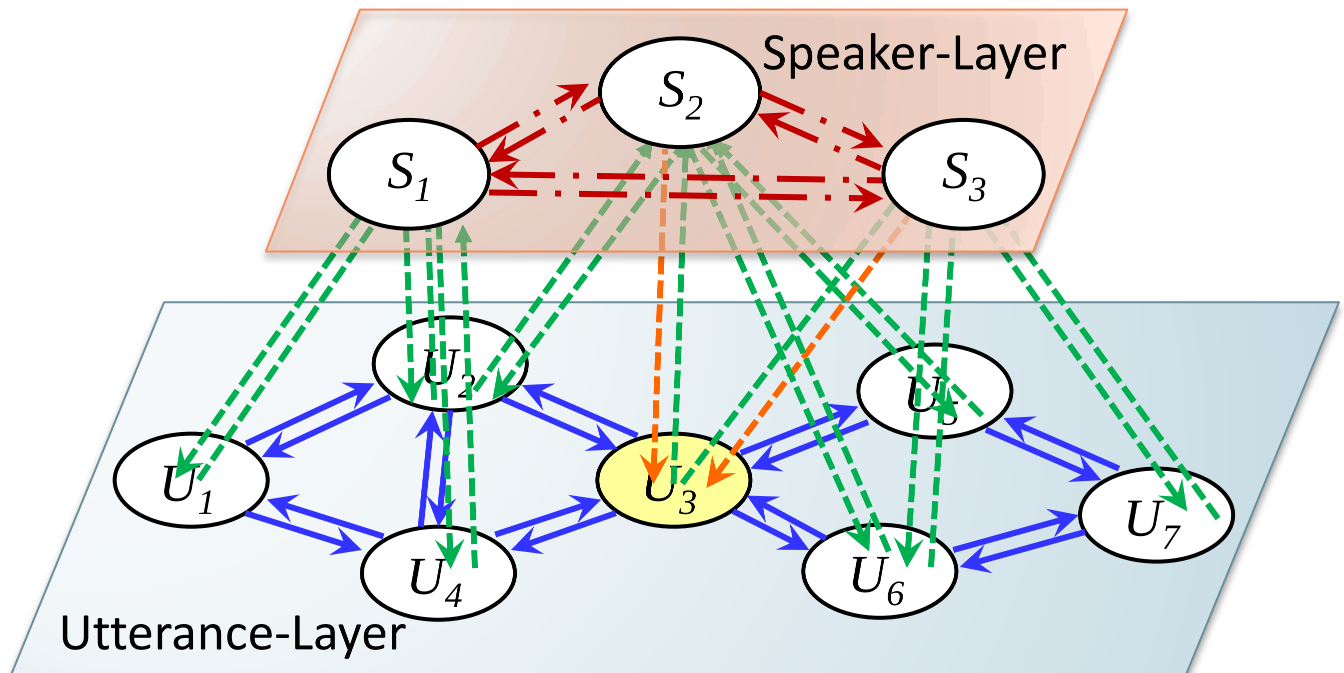

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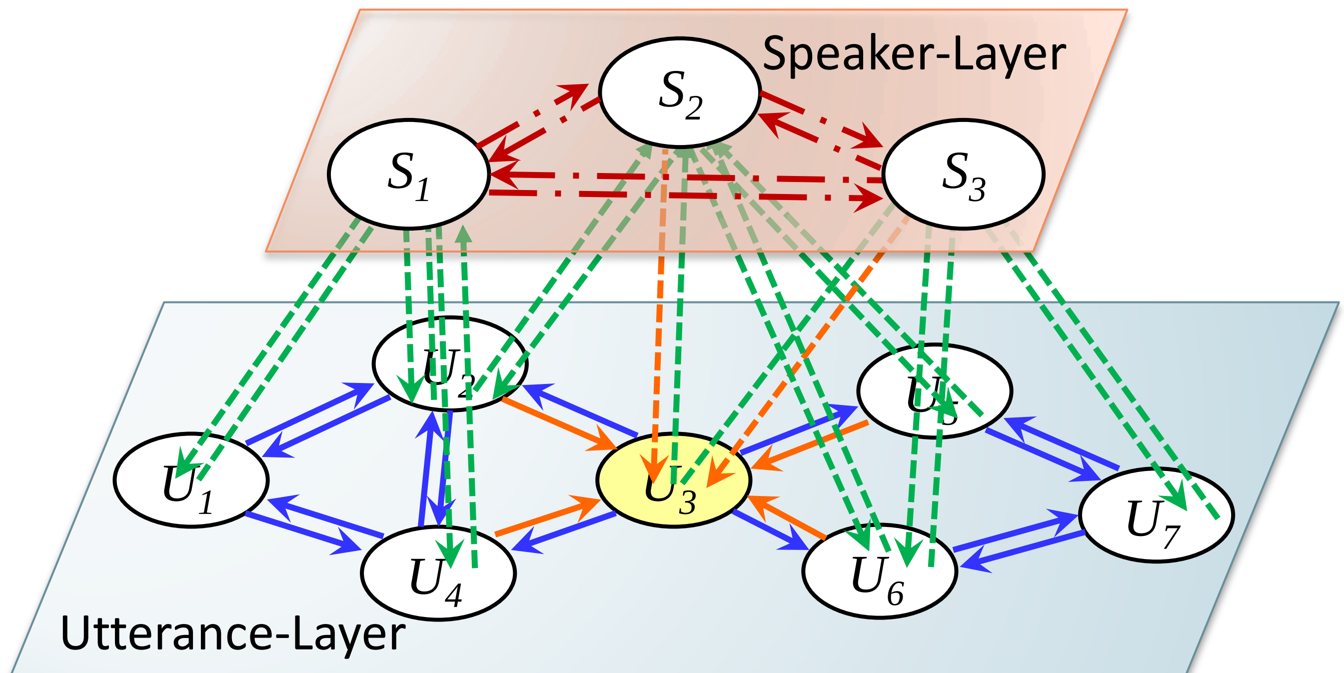

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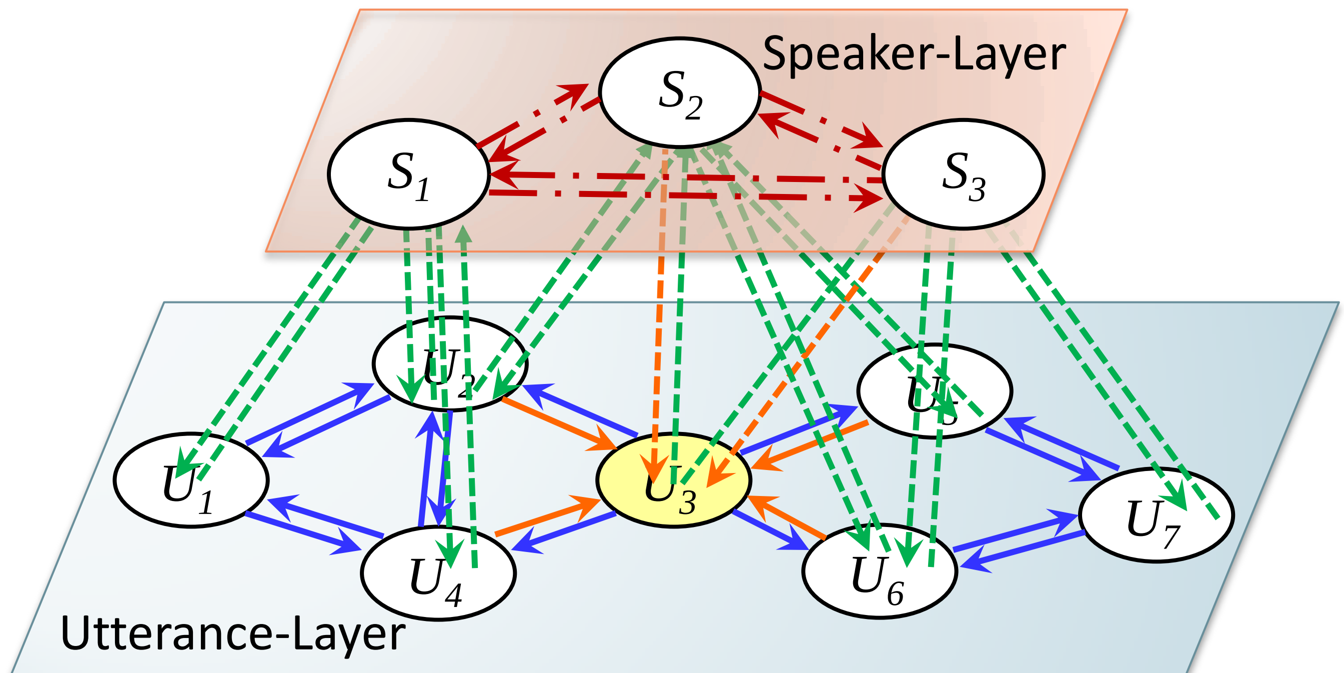

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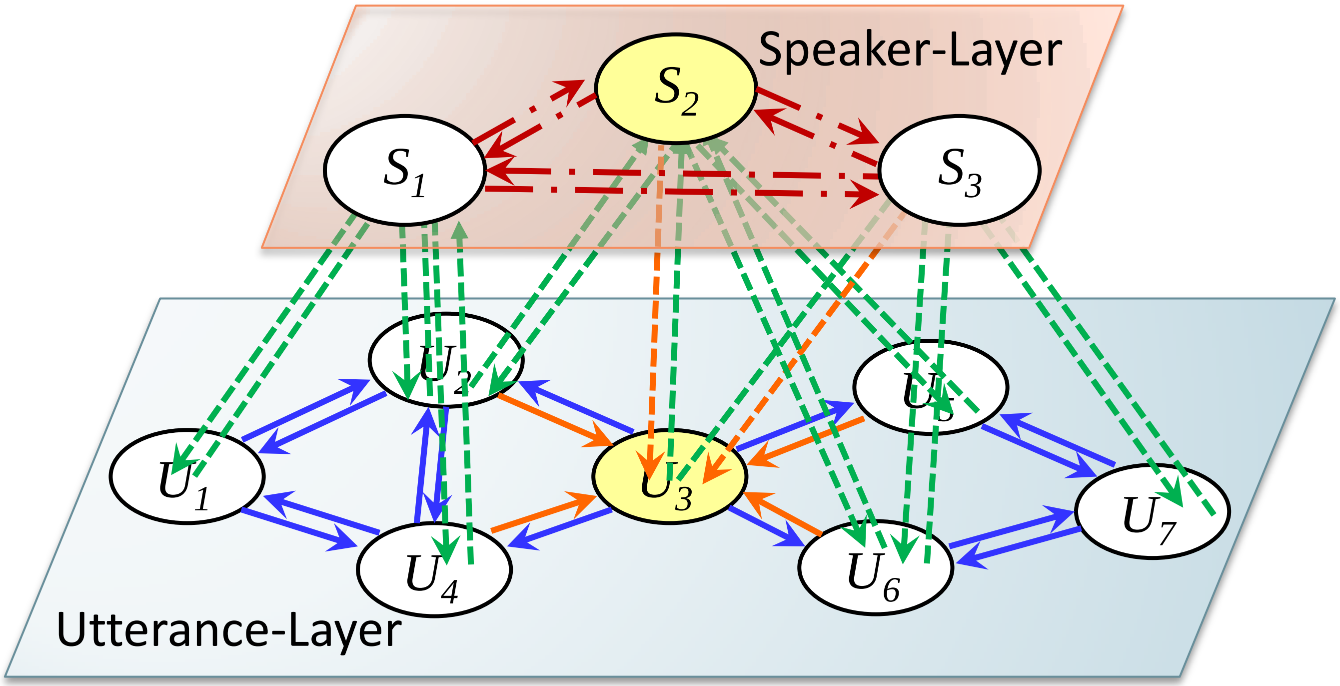

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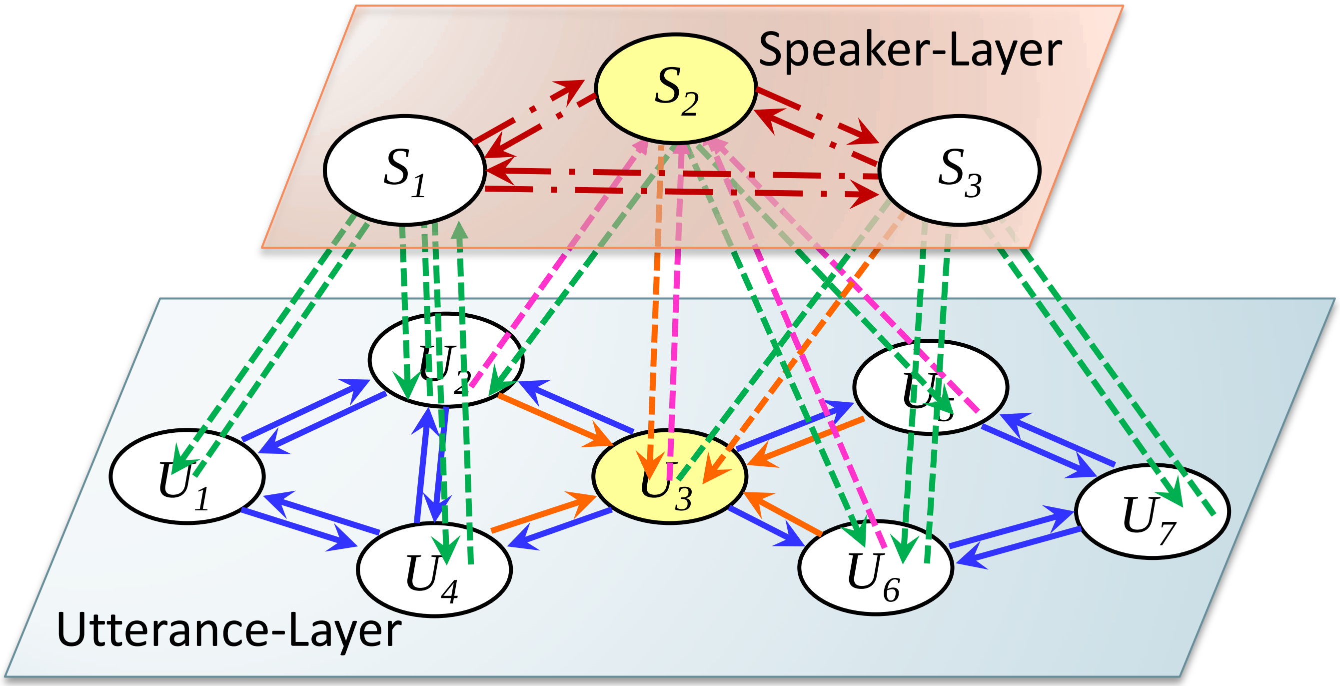

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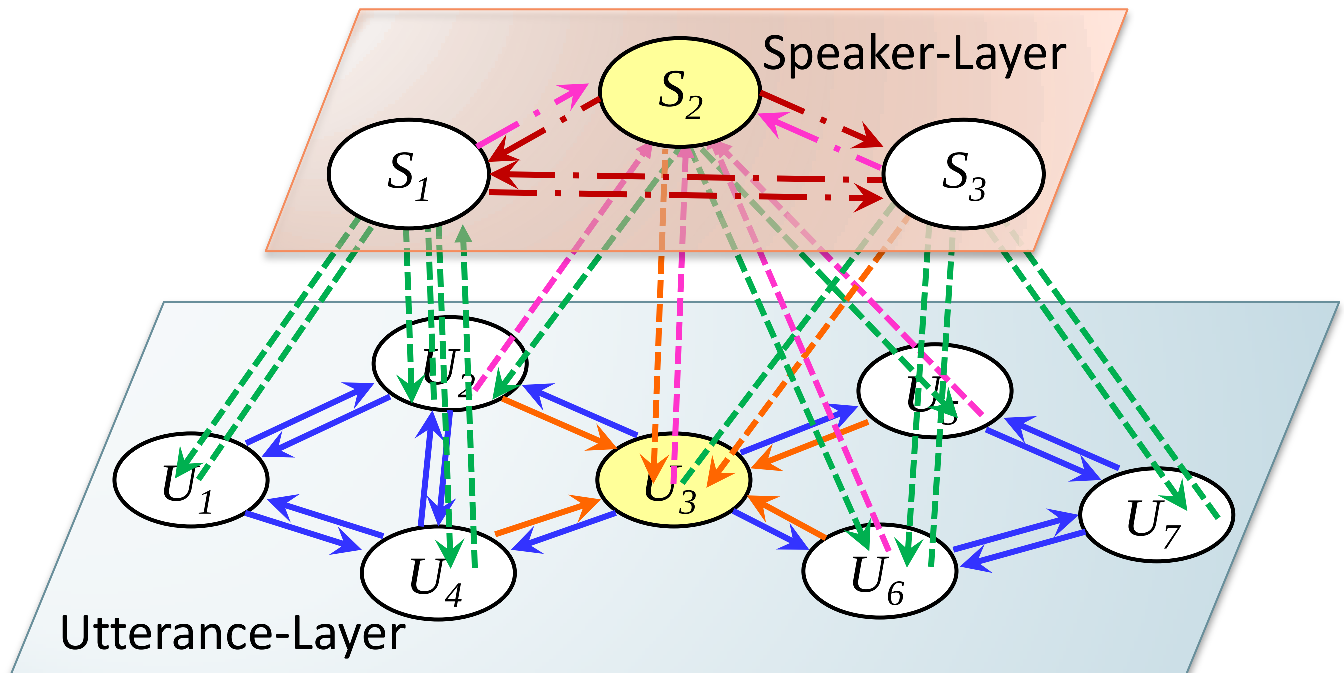

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Utterance node U can get higher score when

① Higher original importance I(U, d)

② More speaker nodes similar to utterance U

③ More important utterances similar to utterance U

- Converged Solution

$$\begin{aligned} F_U^* &= \left((1-\alpha)F_U^{(0)} e^T + \alpha(1-\alpha) L_{UU}^T L_{US} F_S^{(0)} e^T + \alpha^2 L_{UU}^T L_{US} L_{SS}^T L_{SU}\right) F_U^* \\ &= M_2 F_U^* \end{aligned}$$

$F_U$* (final utterance scores) is the dominate eigenvector of $M_2$

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# Experimental Setup

- CMU Speech Meeting Corpus
  - 10 meetings from 2006/04 – 2006/06
  - #Speaker: 6 (total), 2-4 (each meeting)
  - WER = 44%
- Reference Summaries
  - Manually labeled by two annotators
- Parameter Setting
  - α = 0.9
  - Extractive summary ratio = 30%

$$\begin{cases} F_U^{(t+1)} = (1-\alpha)F_U^{(0)} + \boxed{\alpha} \cdot L_{US} F_S^{(t)} \\ F_S^{(t+1)} = (1-\alpha)F_S^{(0)} + \boxed{\alpha} \cdot L_{SU} F_U^{(t)} \end{cases}$$

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# Evaluation Metrics

- ROUGE
  - ROUGE-1
    - F-measure of matched unigram between extracted summary and reference summary
  - ROUGE-L (Longest Common Subsequence)
    - F-measure of matched LCS between extracted summary and reference summary

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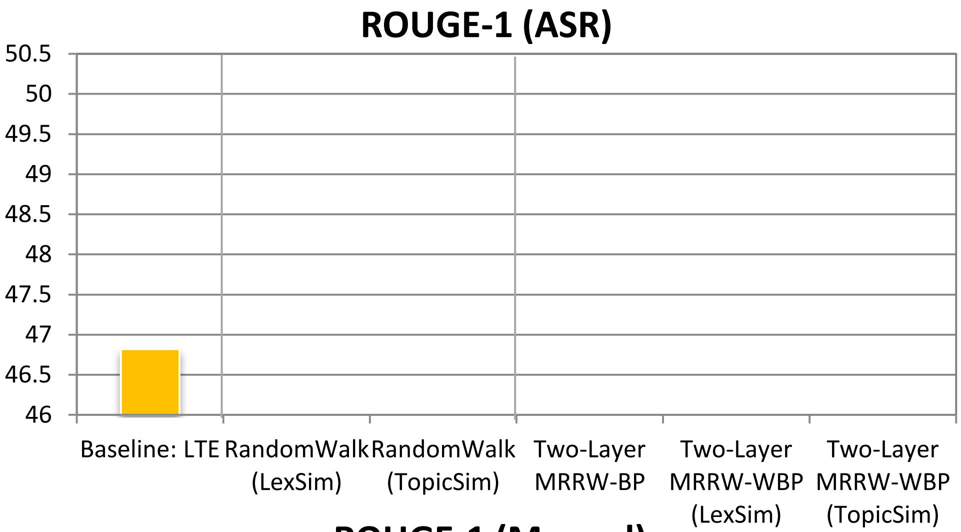
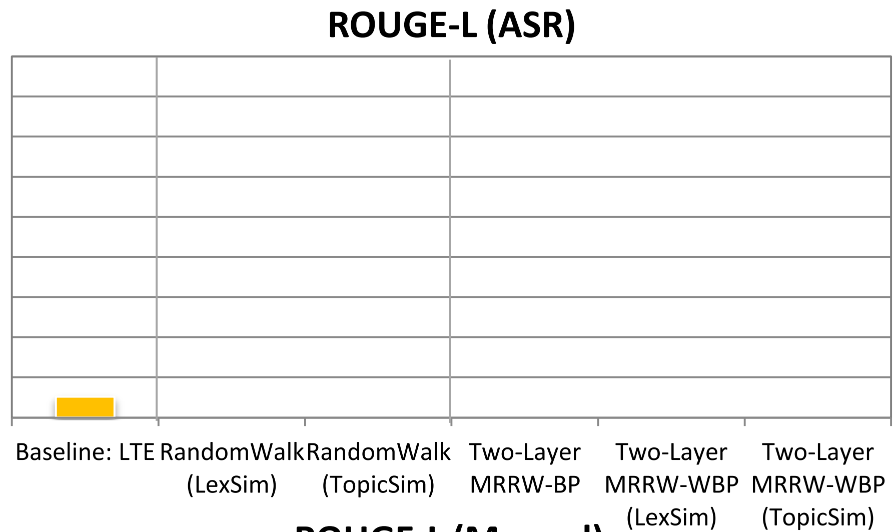
# Results


ROUGE-1 (ASR)
50.5
50
49.5
49
48.5
48
47.5
47
46.5
46
Baseline: LTE
RandomWalk (LexSim)
RandomWalk (TopicSim)
Two-Layer MRRW-BP
Two-Layer MRRW-WBP (LexSim)
Two-Layer MRRW-WBP (TopicSim)


ROUGE-L (ASR)
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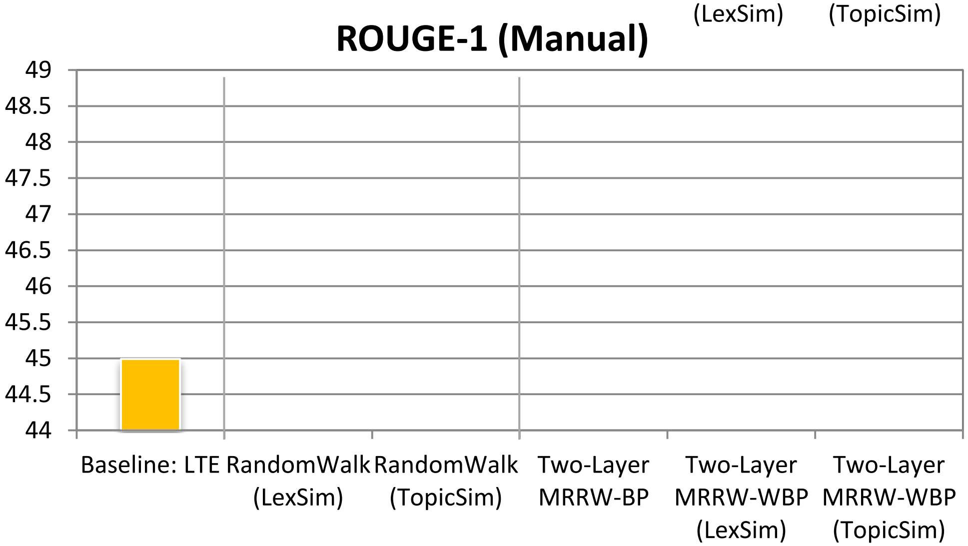
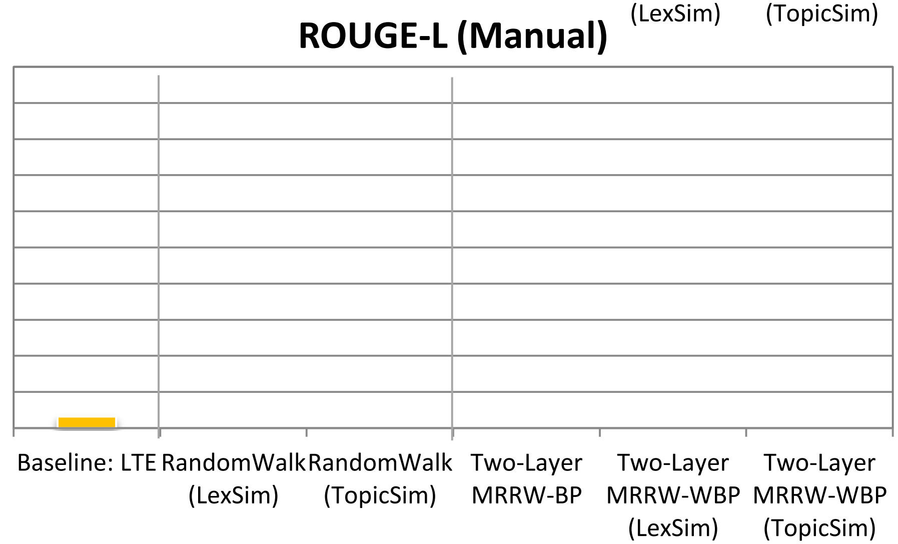
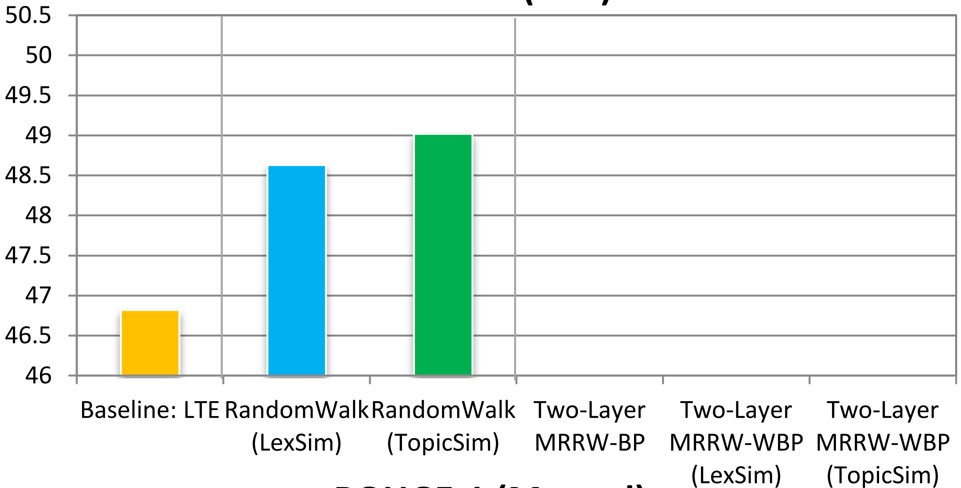
Two-Layer MRRW-BP
Two-Layer MRRW-WBP (LexSim)
Two-Layer MRRW-WBP (TopicSim)


ROUGE-1 (Manual)
49
48.5
48
47.5
47
46.5
46
45.5
45
44.5
44
Baseline: LTE
RandomWalk (LexSim)
RandomWalk (TopicSim)
Two-Layer MRRW-BP
Two-Layer MRRW-WBP (LexSim)
Two-Layer MRRW-WBP (TopicSim)

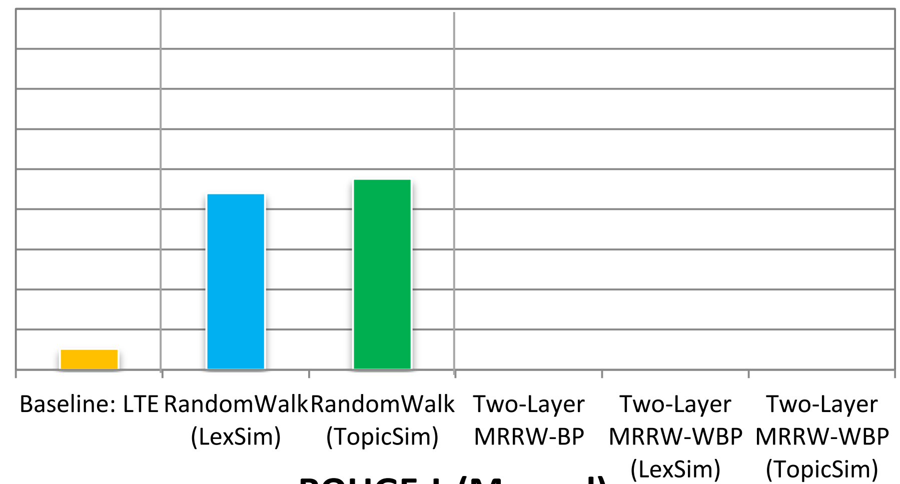

ROUGE-L (Manual)
Baseline: LTE
RandomWalk (LexSim)
RandomWalk (TopicSim)
Two-Layer MRRW-BP
Two-Layer MRRW-WBP (LexSim)
Two-Layer MRRW-WBP (TopicSim)

# Results – Baseline & Single-Layer Graph Approaches

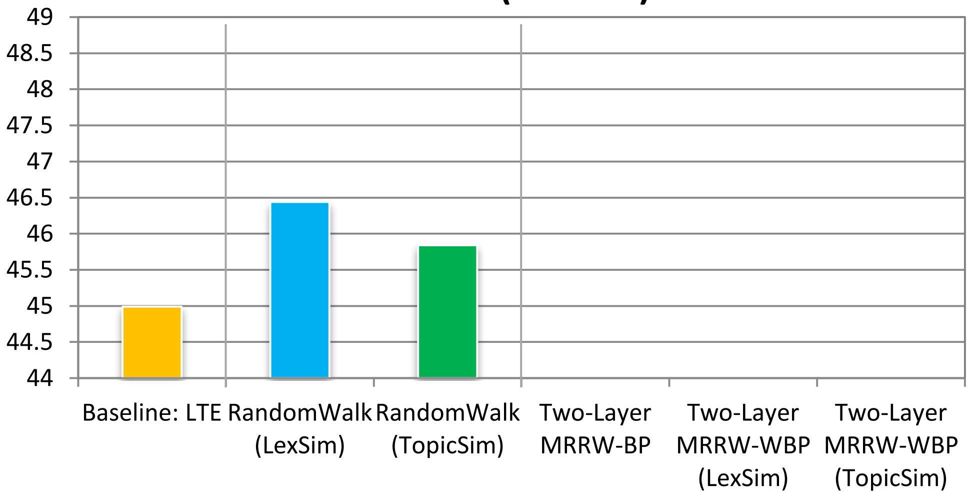
**ROUGE-1 (ASR)**



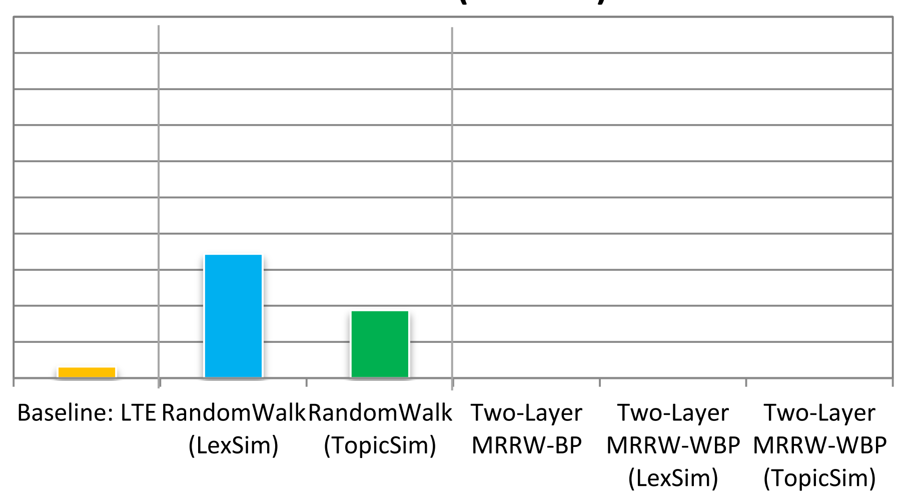

**ROUGE-L (ASR)**




**ROUGE-1 (Manual)**



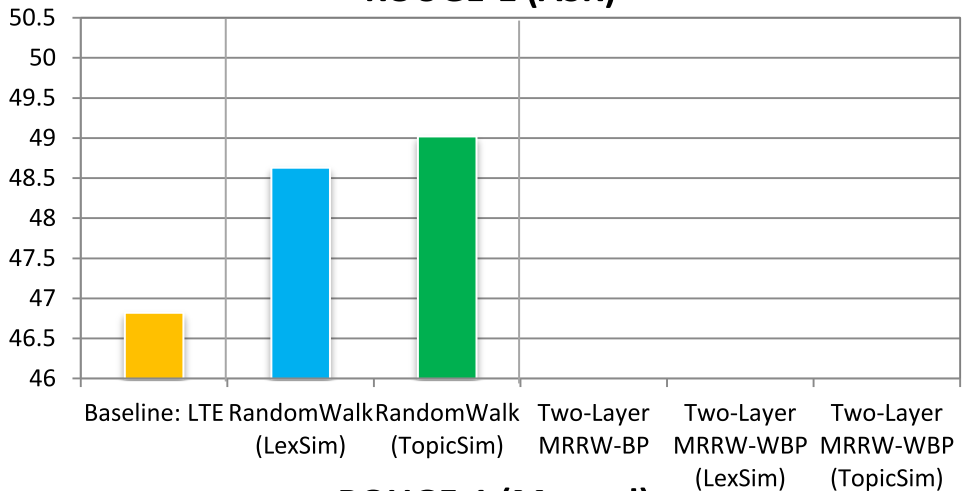

**ROUGE-L (Manual)**



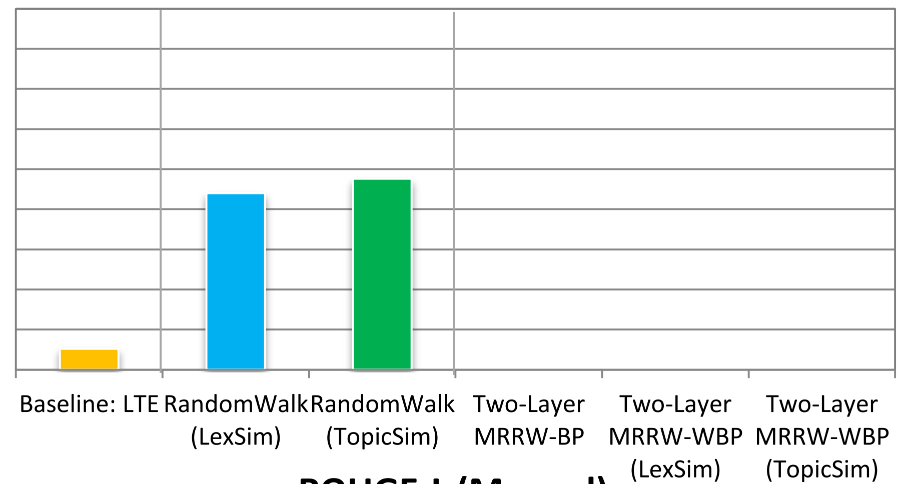

Graph-based approaches are significantly better than baseline

# Results – Baseline & Single-Layer Graph Approaches

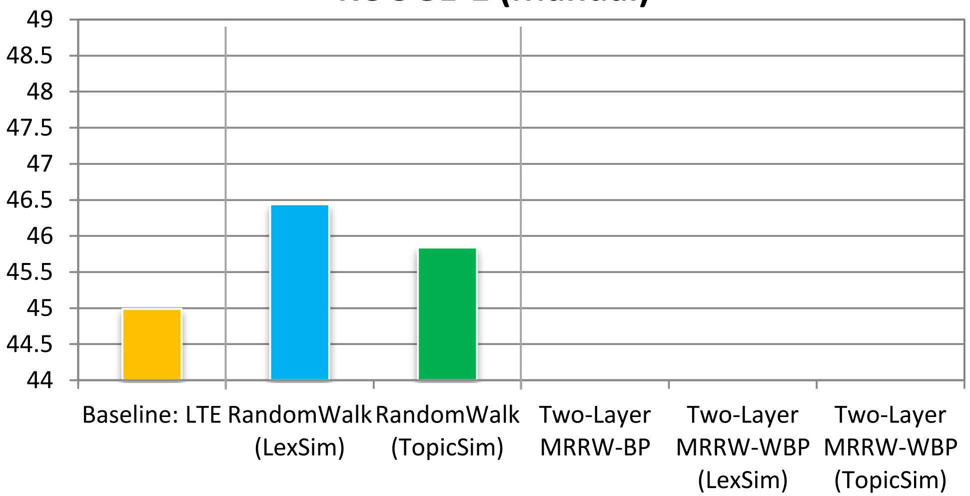
ROUGE-1 (ASR)



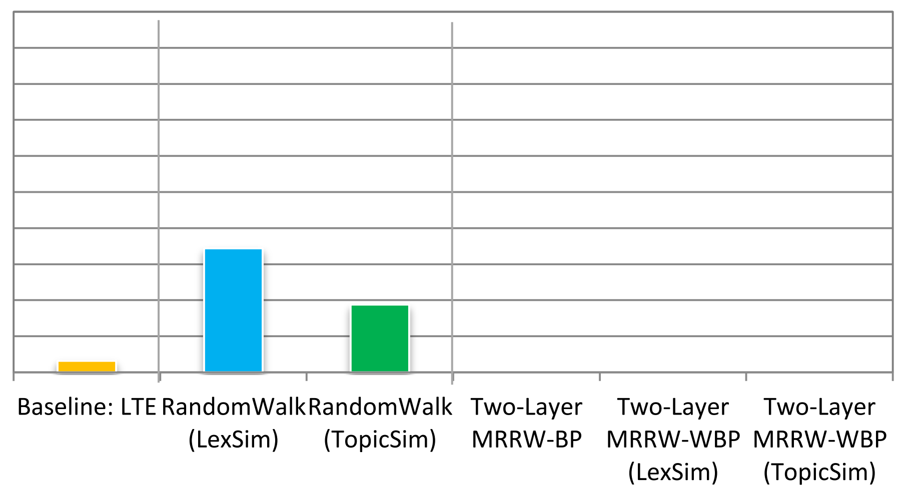

ROUGE-L (ASR)




ROUGE-1 (Manual)



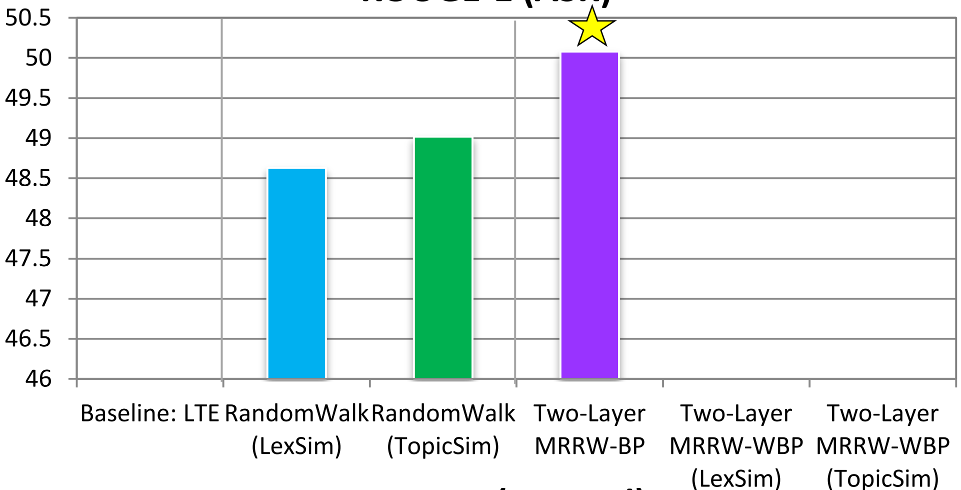

ROUGE-L (Manual)



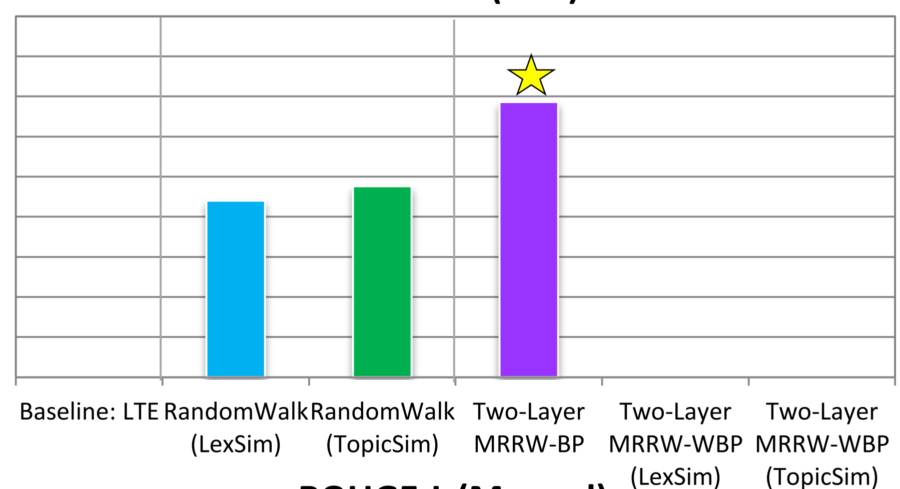

Improvement for ASR is larger than manual transcripts due to recognition errors

# Results – Single- & Two-Layer Graph Approaches

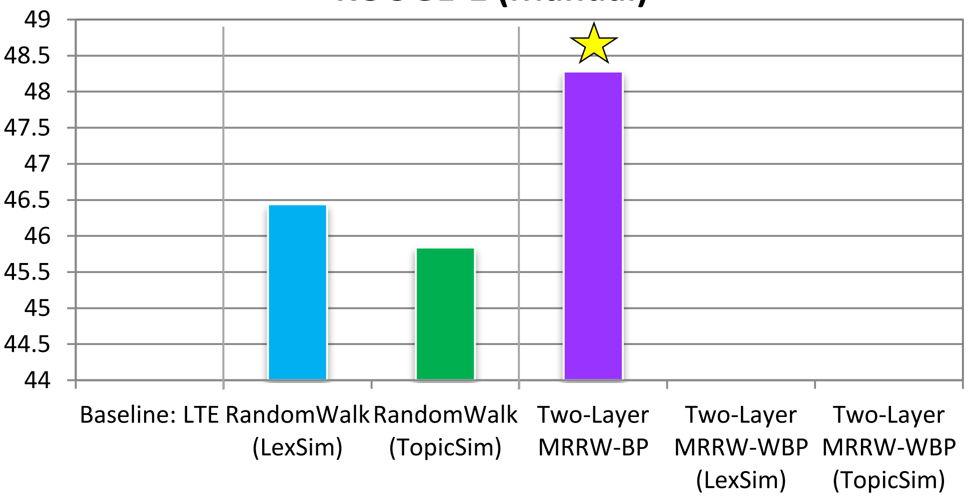
**ROUGE-1 (ASR)**



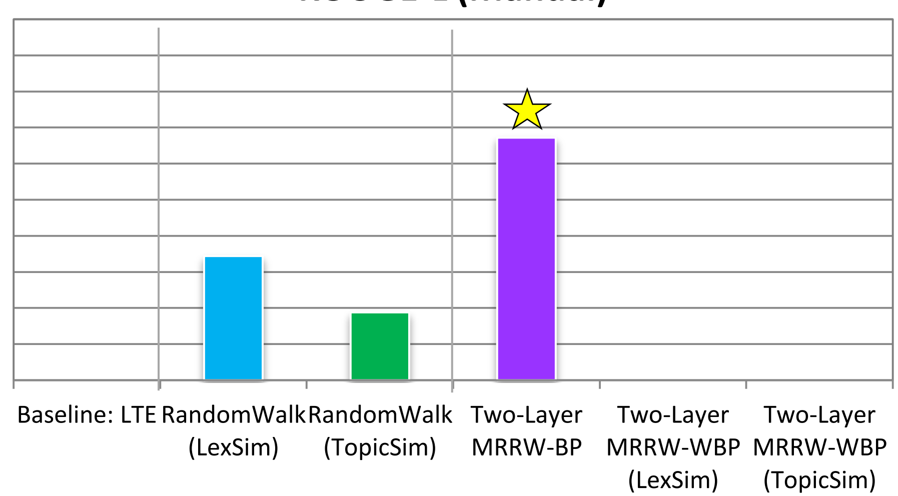

**ROUGE-L (ASR)**




**ROUGE-1 (Manual)**

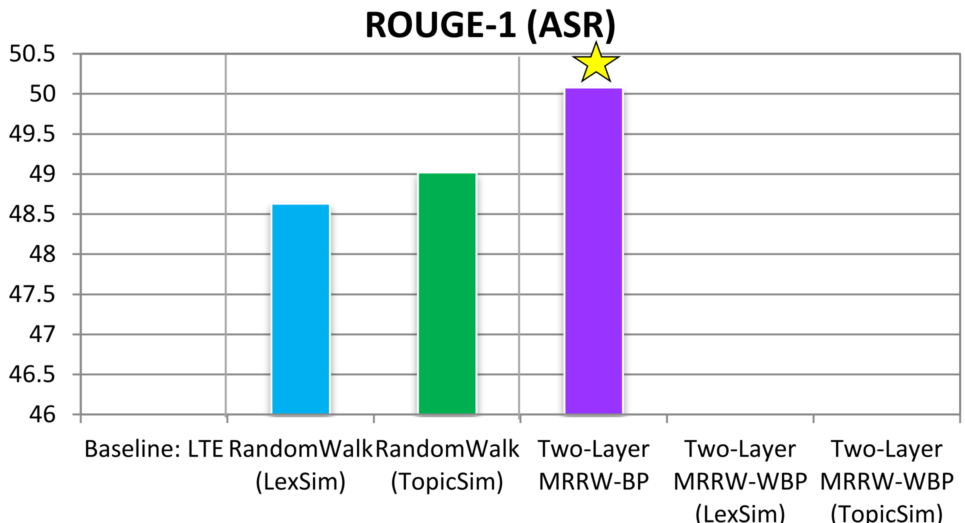


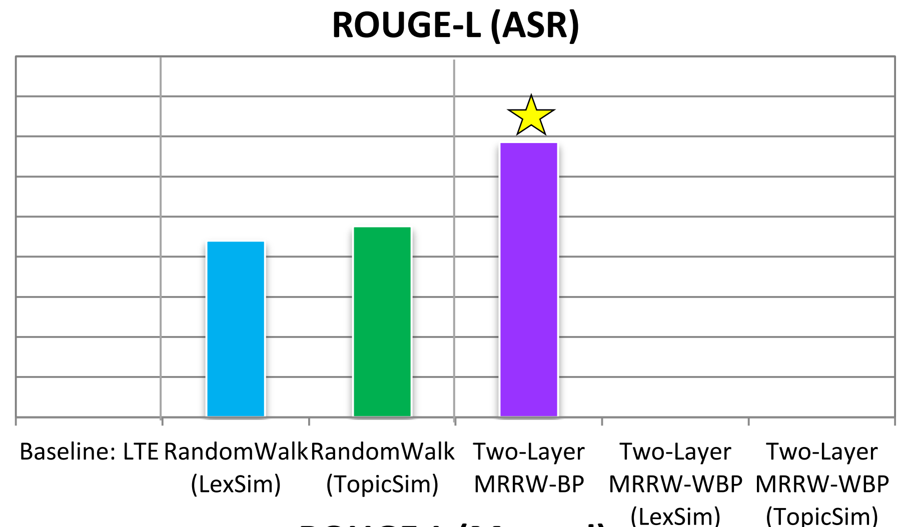

**ROUGE-L (Manual)**

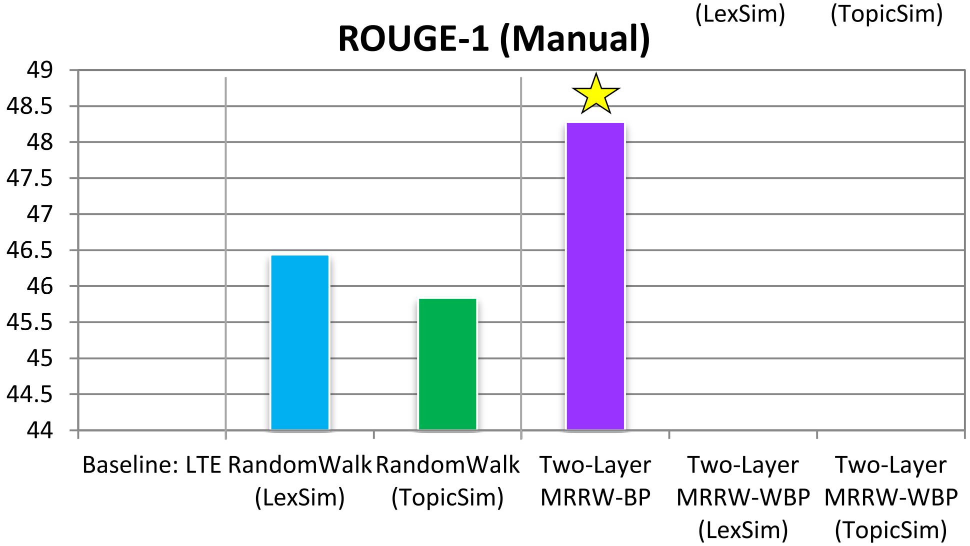


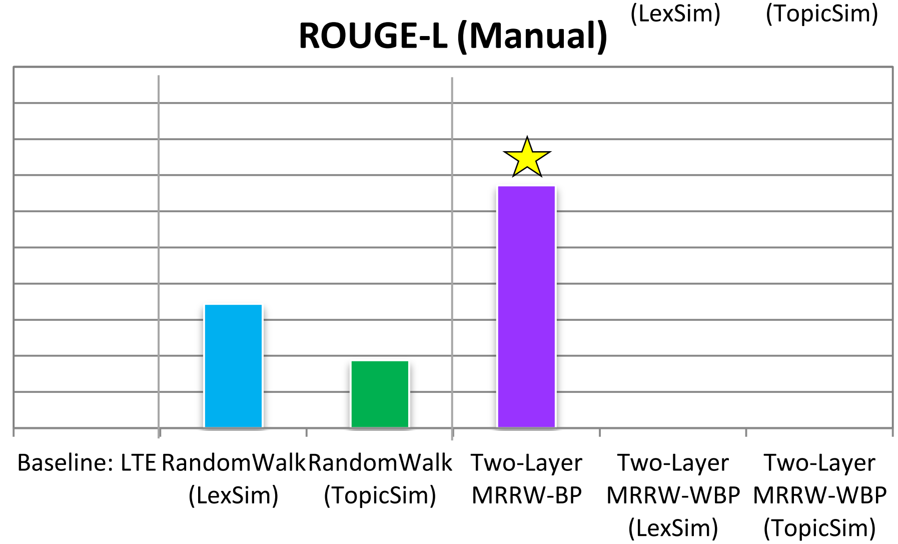

Two-layer approaches involving speaker info. outperform single-layer approaches

# Results – Single- & Two-Layer Graph Approaches



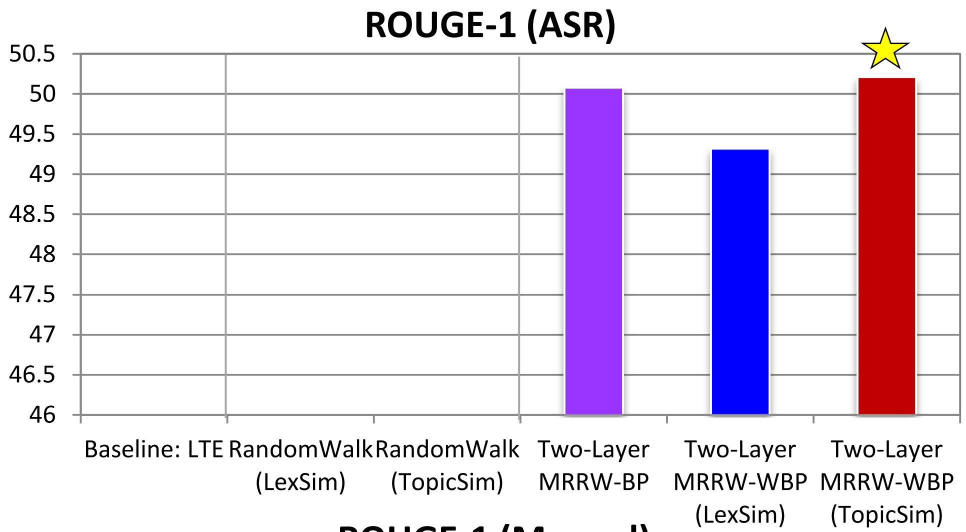



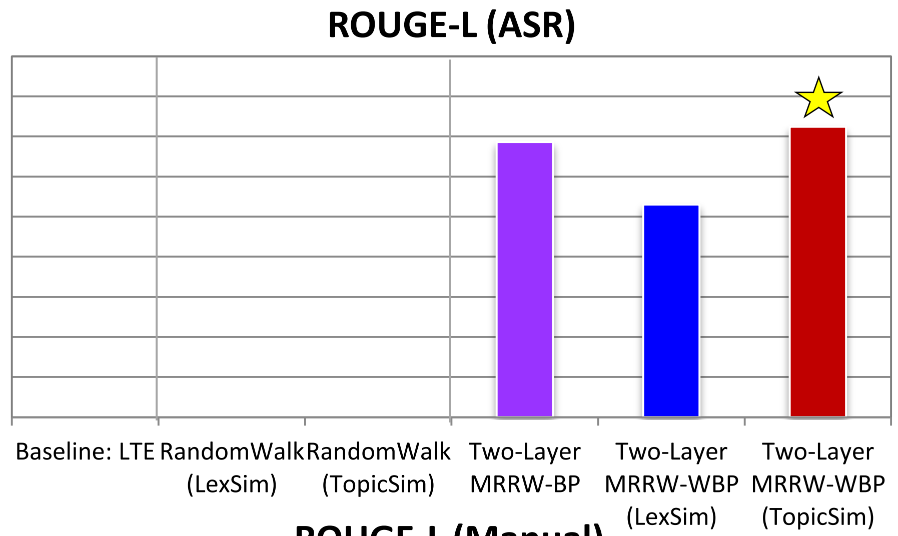



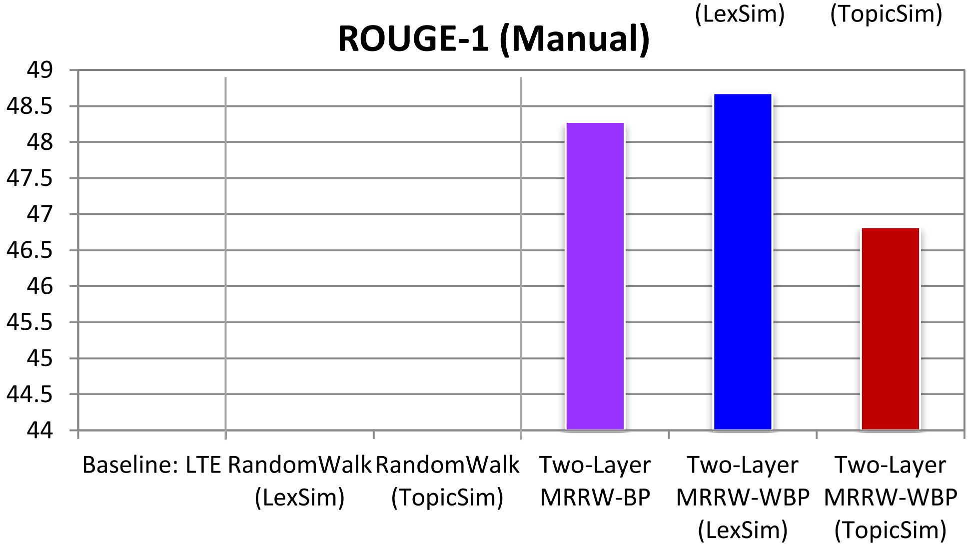



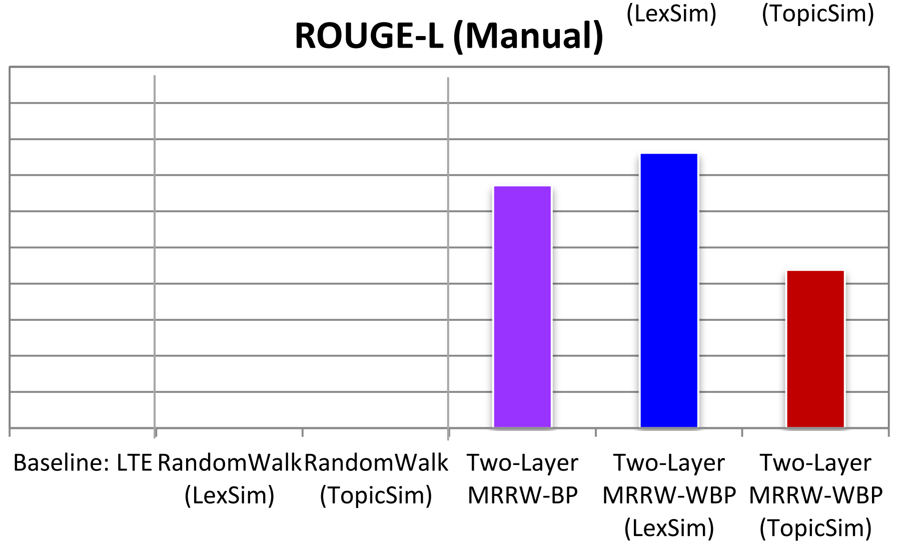

The utterances from the speakers who speak more important utterances tend to be more important

# Results – Effectiveness of Within-Layer Propagation



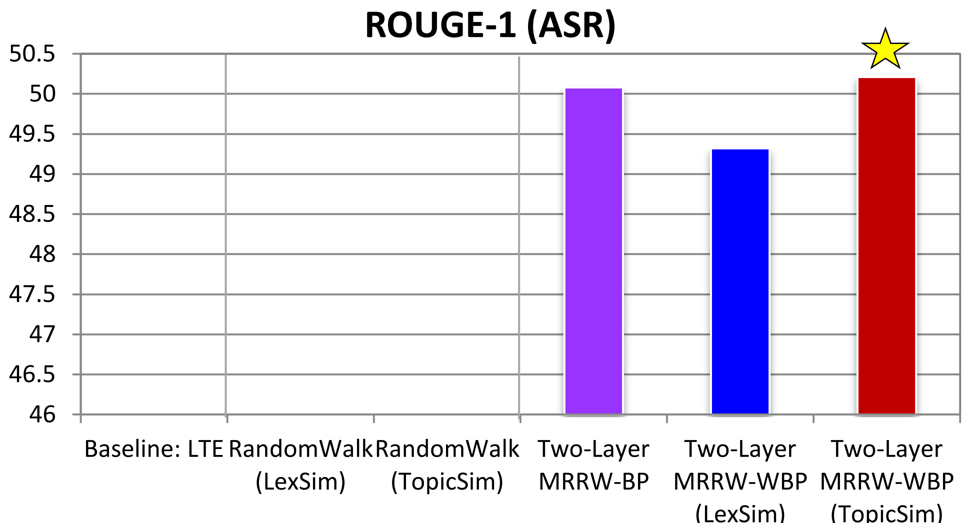



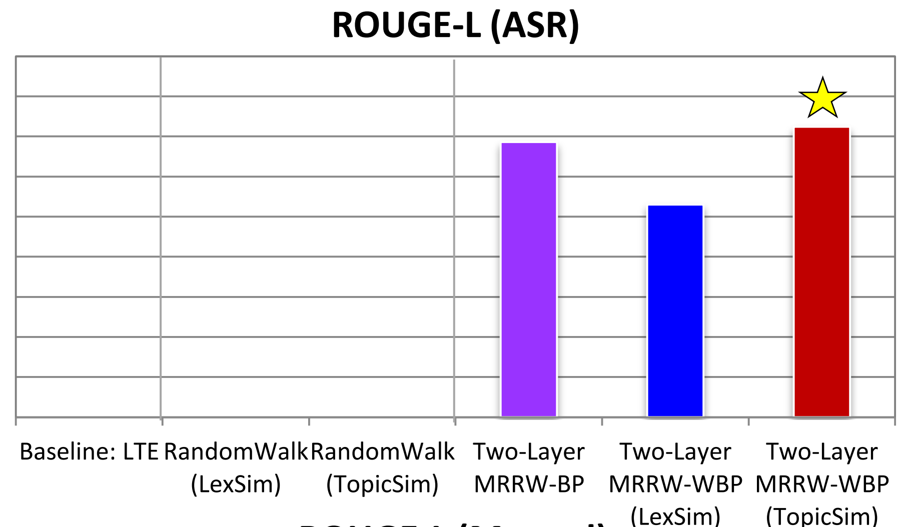



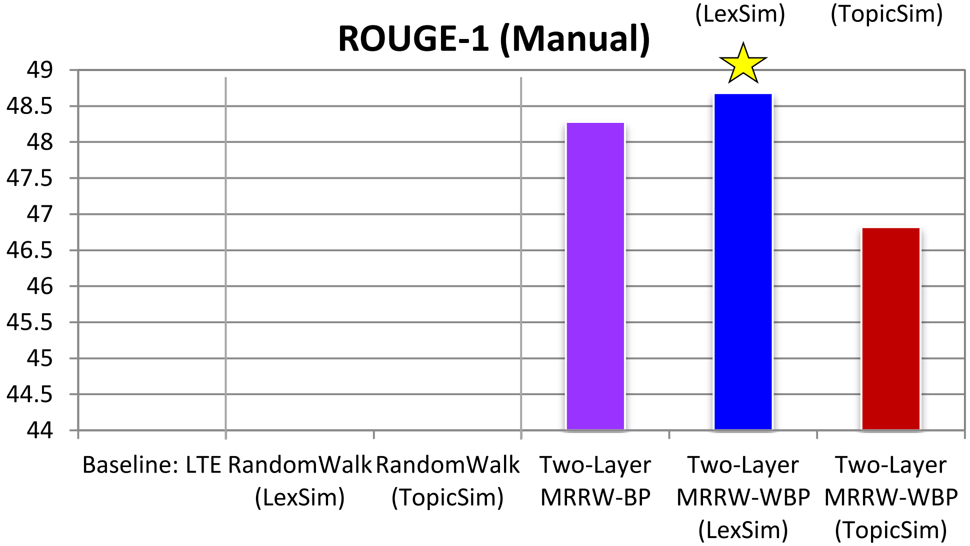



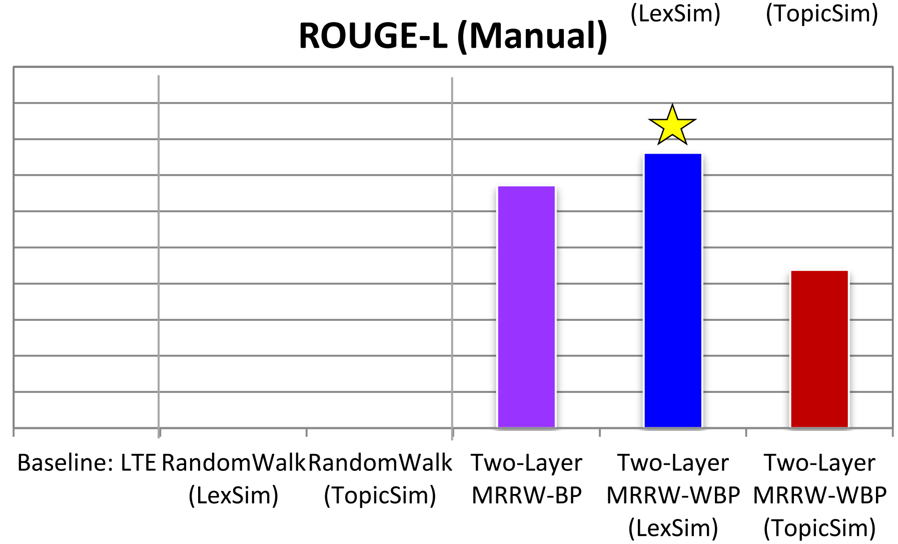

For ASR transcripts, within-layer propagation using topical similarity is better

# Results – Effectiveness of Within-Layer Propagation



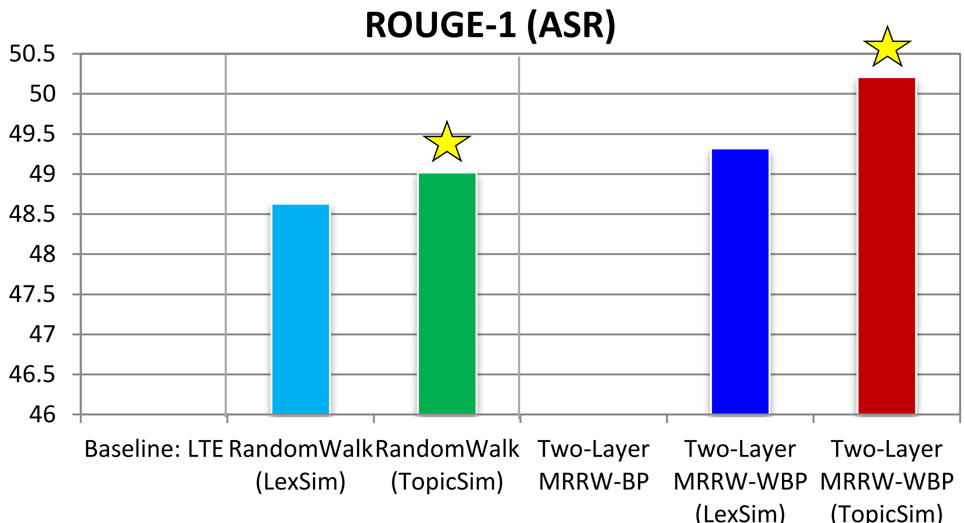



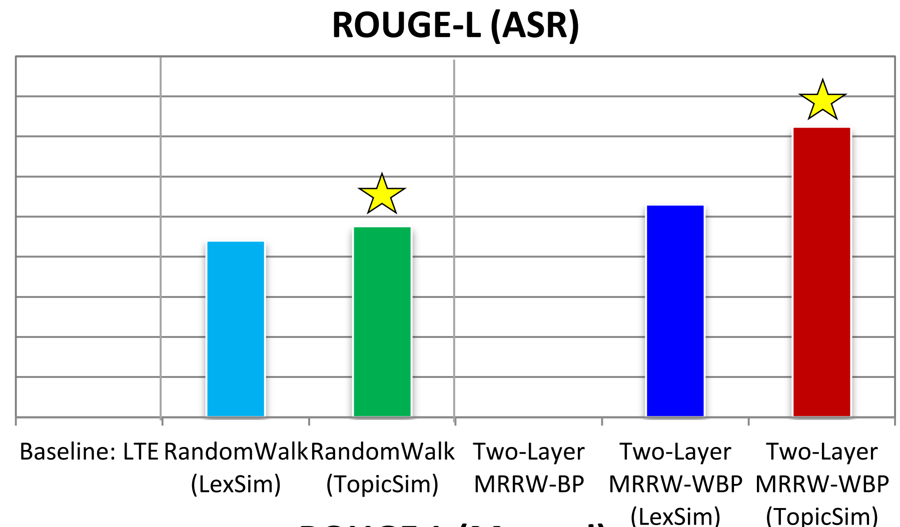



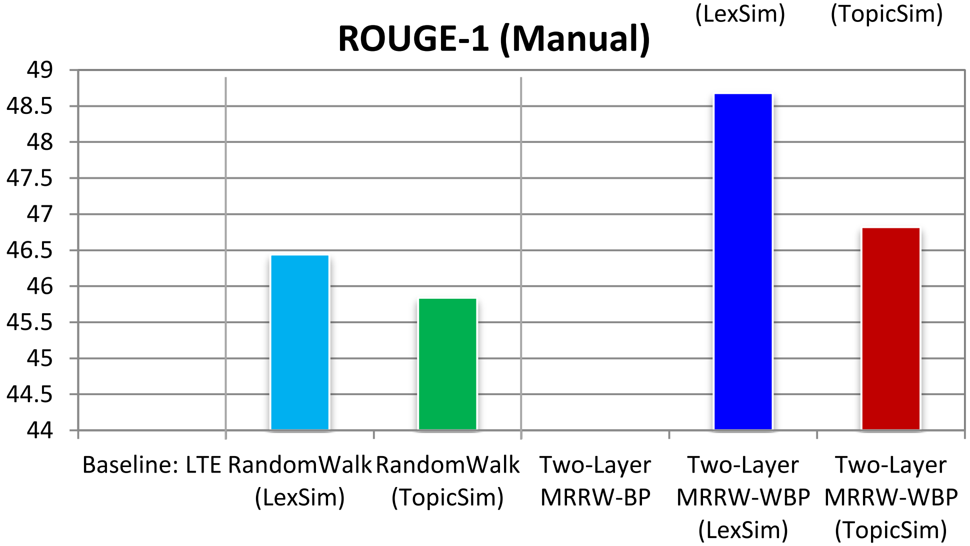



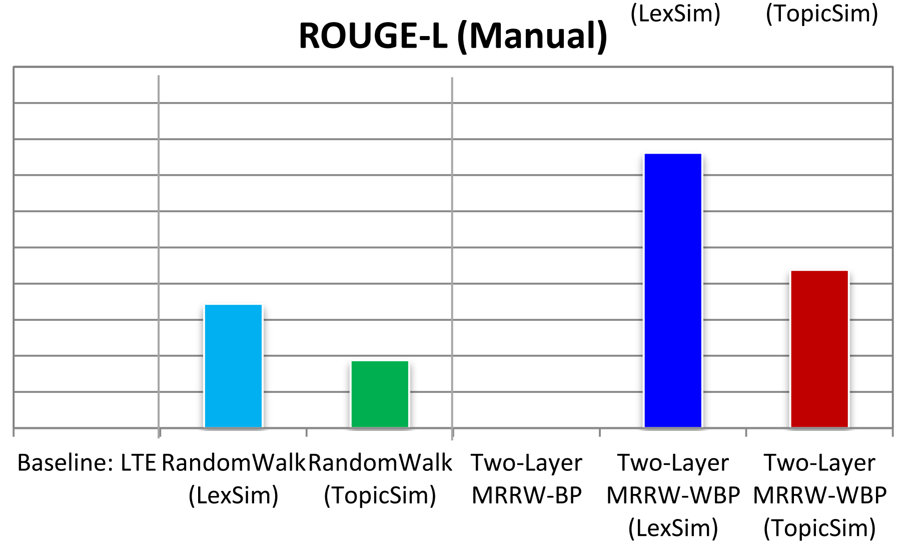

For manual transcripts, within-layer propagation using lexical similarity is better

# Results – Lexical & Topical Similarity



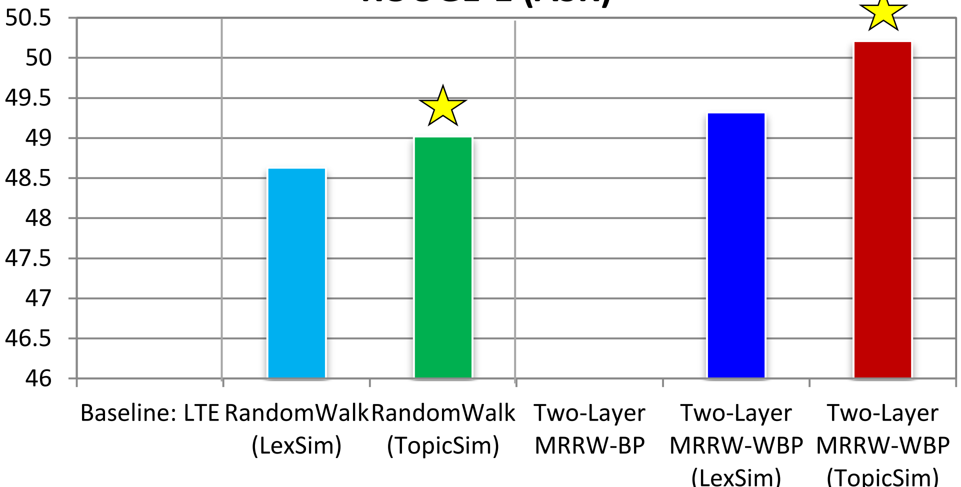



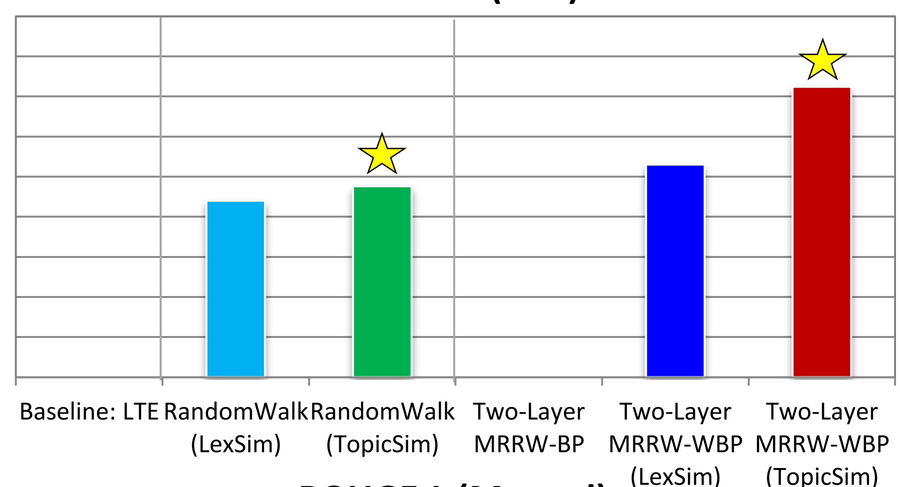

For ASR transcripts, topical similarity outperforms lexical similarity in both cases

# Results – Lexical & Topical Similarity

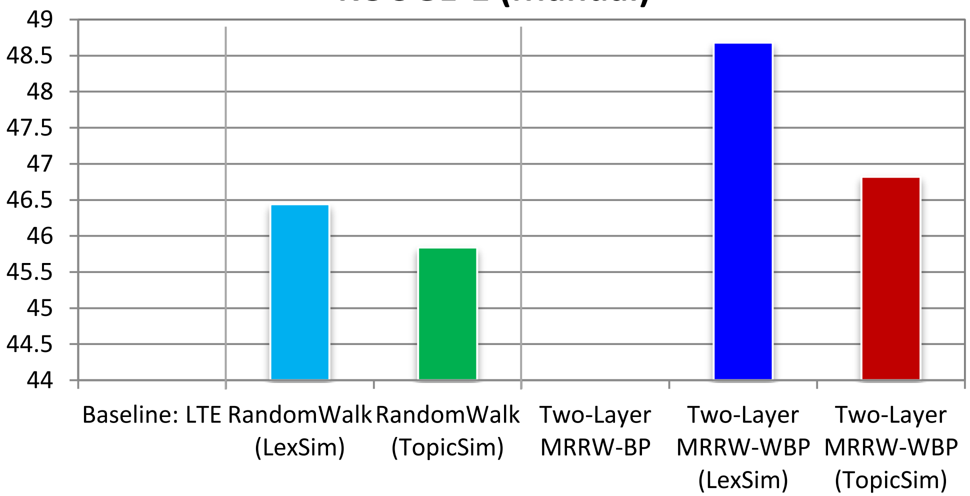
**ROUGE-1 (ASR)**



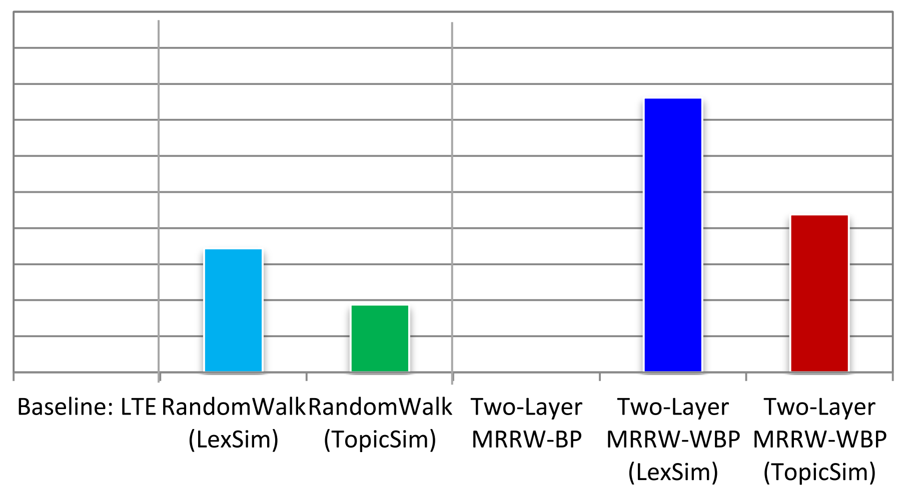

**ROUGE-L (ASR)**




**ROUGE-1 (Manual)**

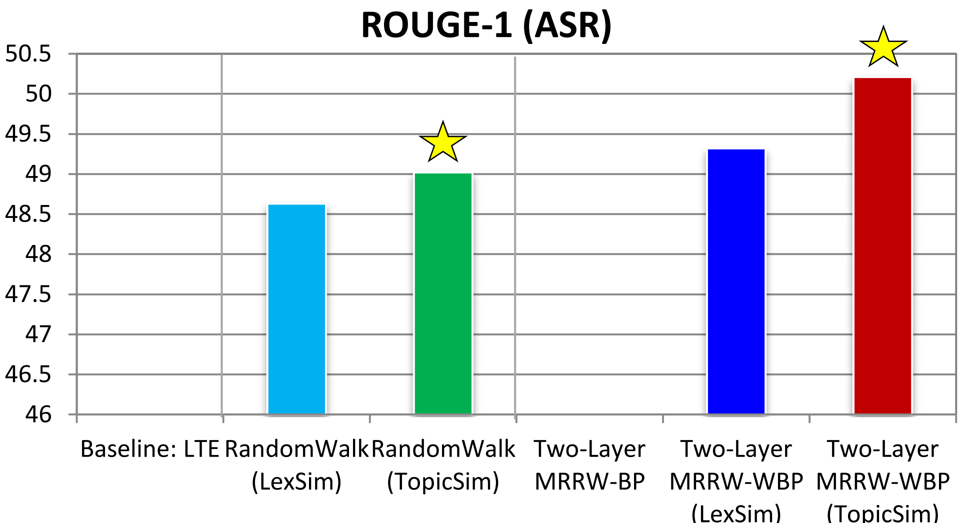


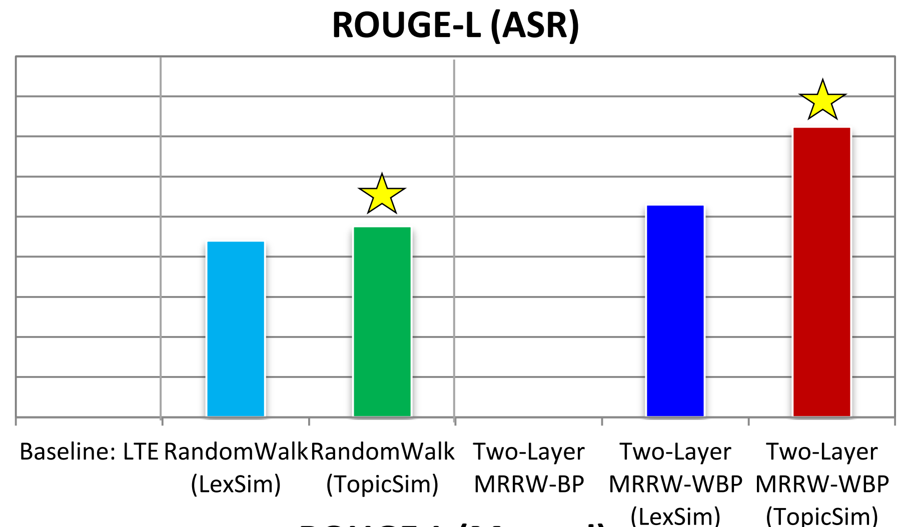

**ROUGE-L (Manual)**

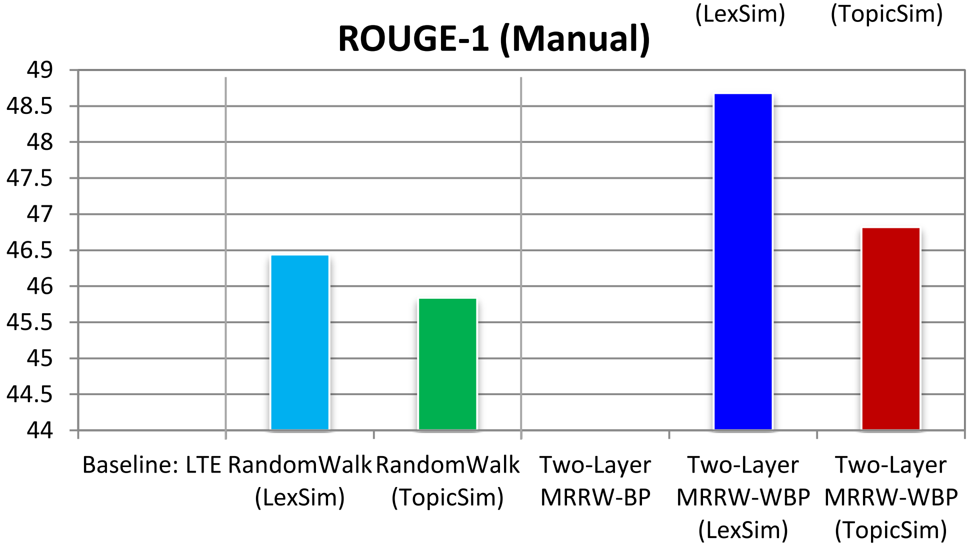


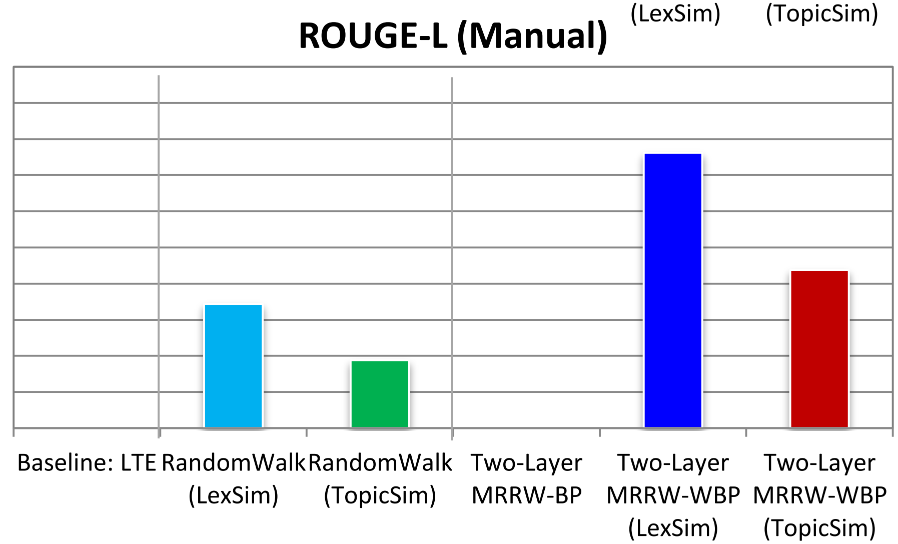

Topical similarity can compensate recognition errors

# Results – Lexical & Topical Similarity



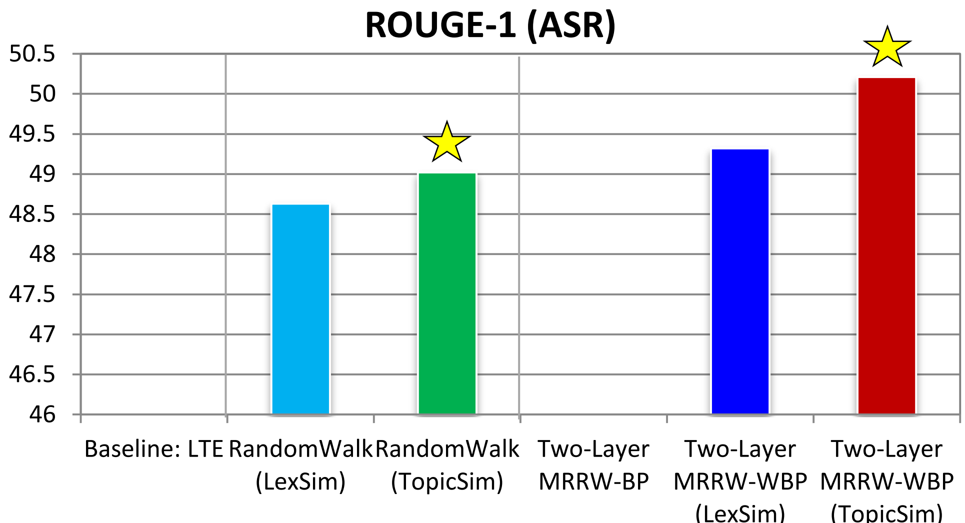



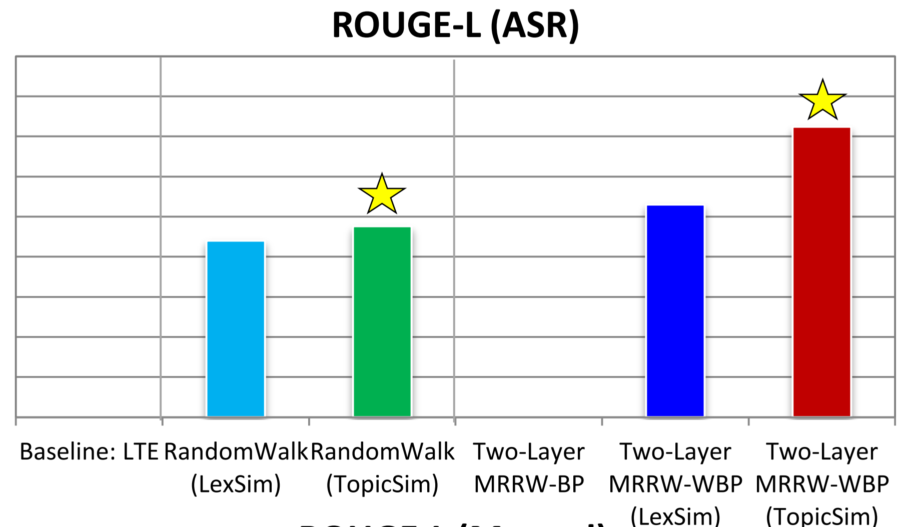



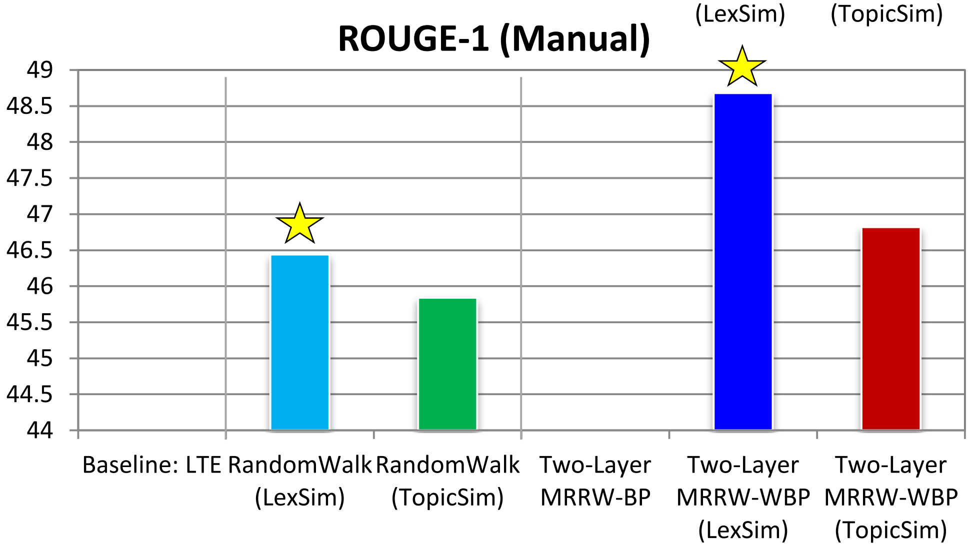



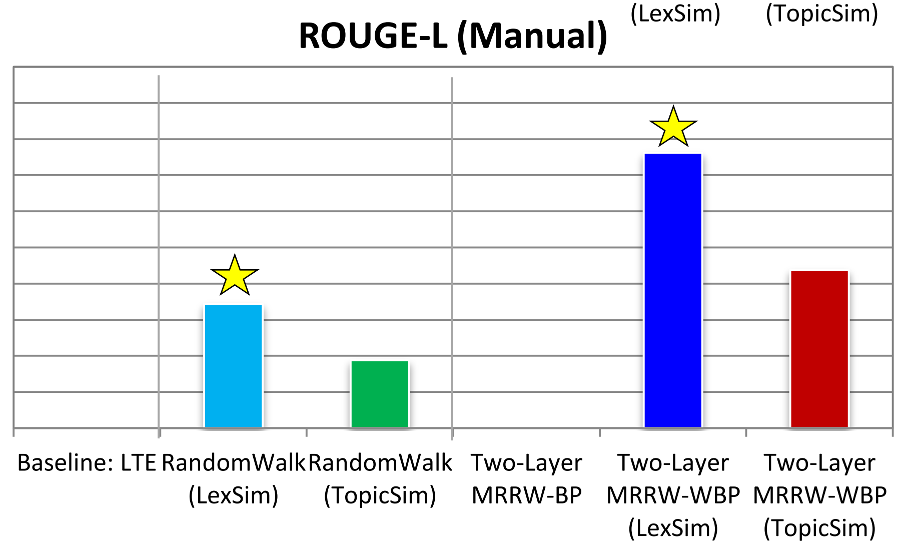

Lexical similarity from word overlap may have some noises due to recognition errors

# Results – Lexical & Topical Similarity



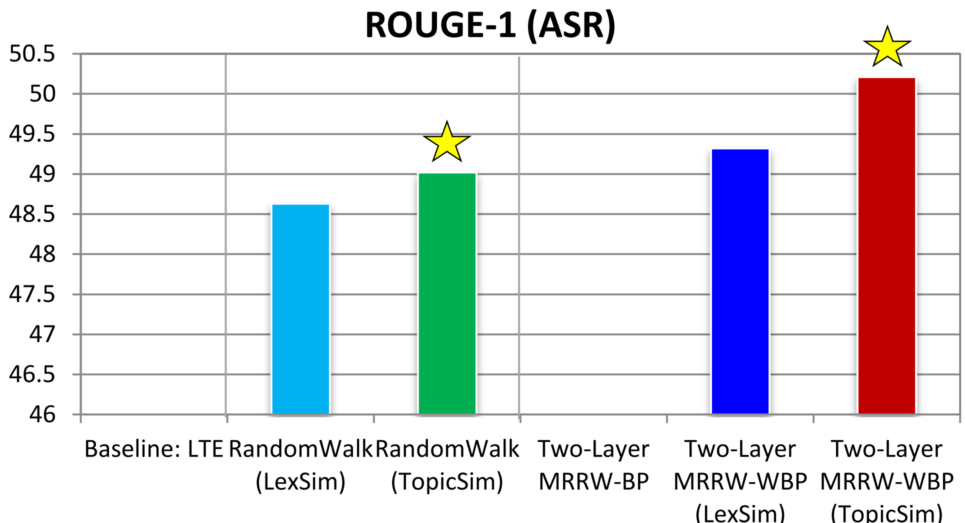



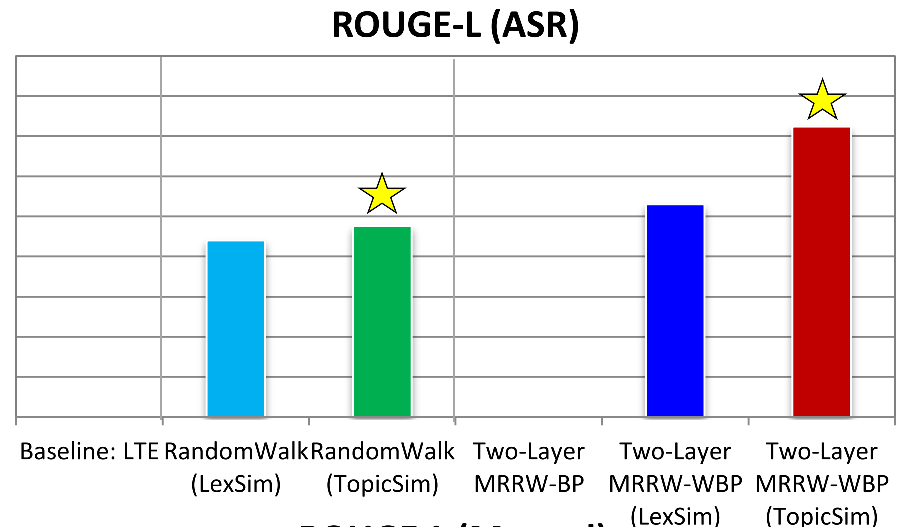



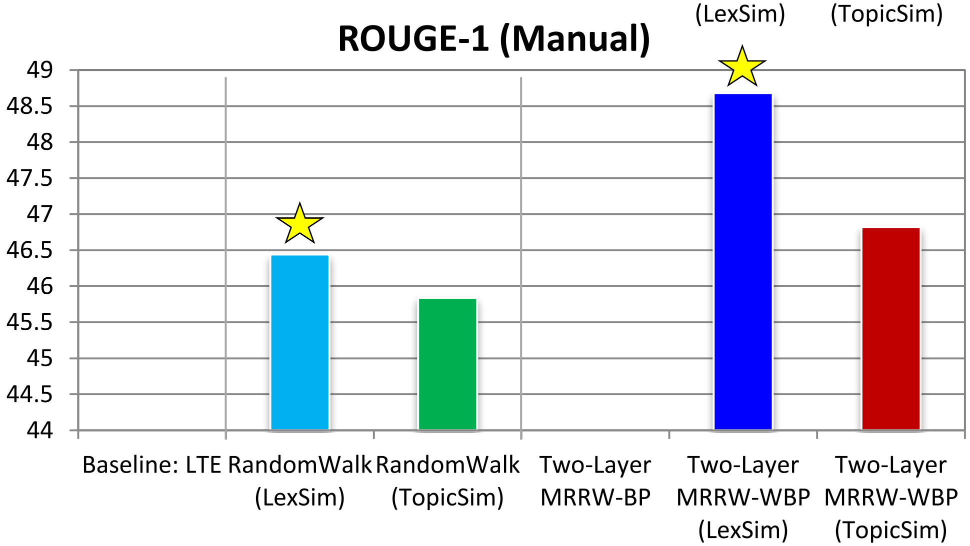



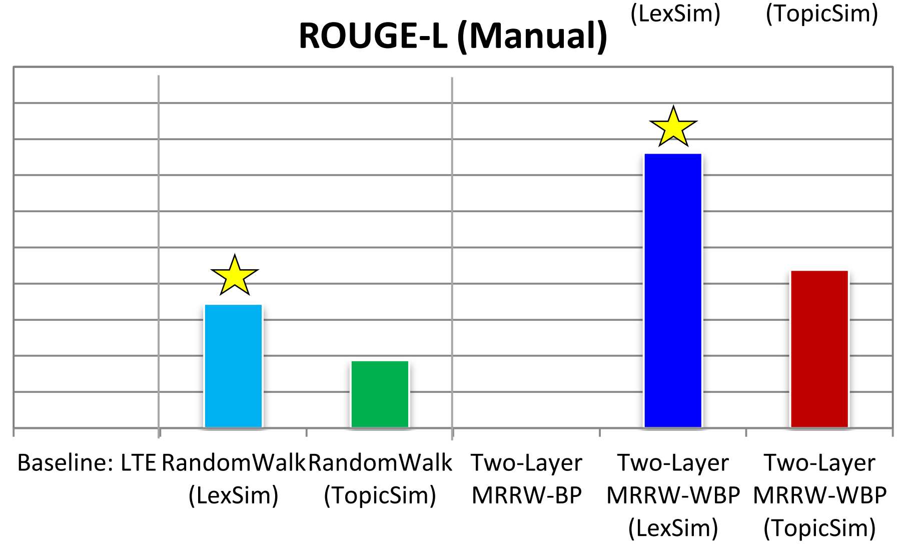

For manual transcripts, lexical similarity outperforms topical similarity in both cases

# Results – Lexical & Topical Similarity



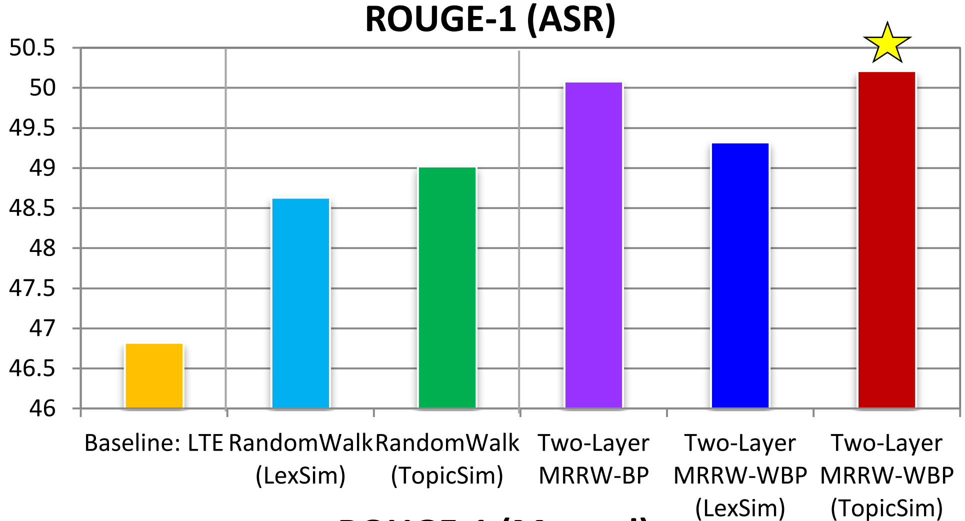



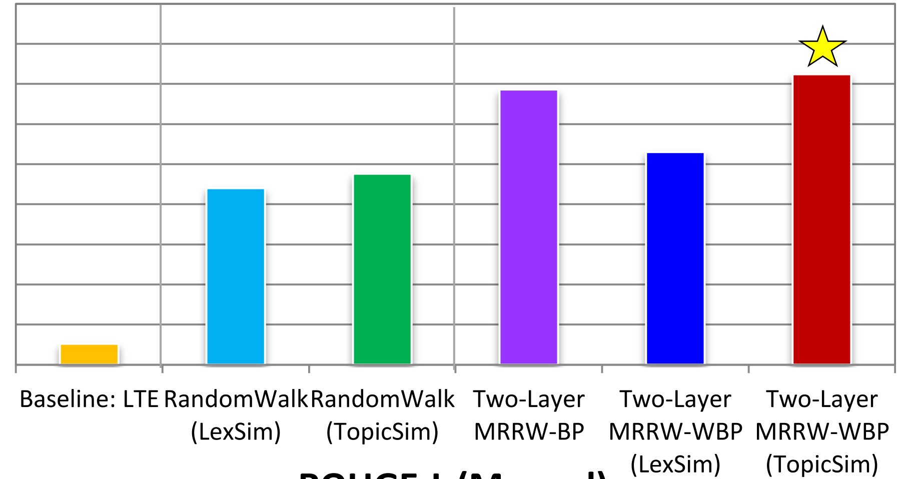

Lexical similarity can model relations accurately since in absence of errors

# Results – All

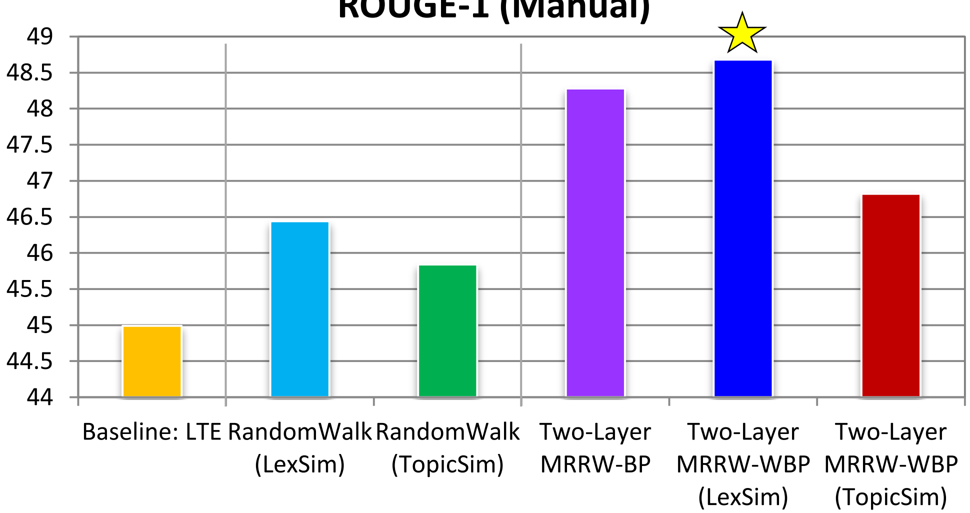
### ROUGE-1 (ASR)




### ROUGE-L (ASR)




### ROUGE-1 (Manual)

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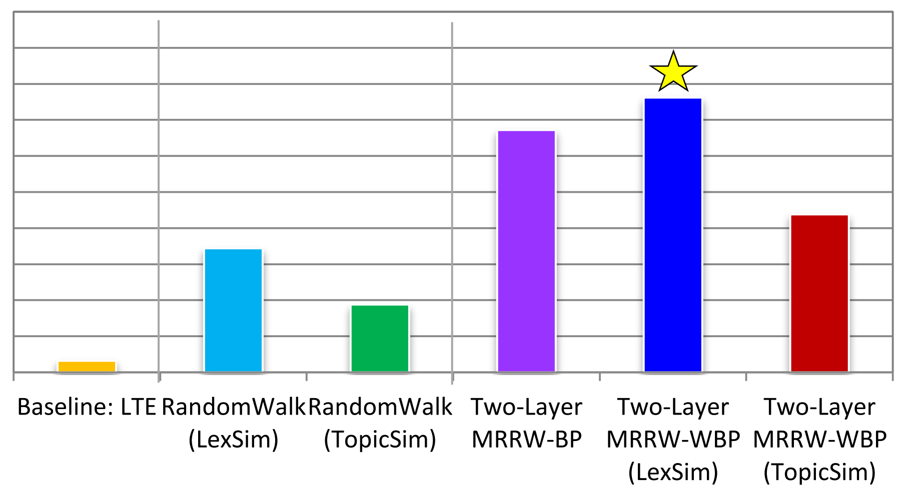


Proposed approaches achieve **7.2%** and **8.2%** relative improvement compared to baseline for ASR and manual respectively

# Outline

Introduction | Approach | Experiments | **Conclusion**

- Graph-based approaches can improve speech summarization performance
- Two-layer approaches involving speaker information can get further improvement
- Topical similarity is more robust to recognition errors

  → better for ASR transcripts
- Lexical similarity is more accurate when absence of errors

  → better for manual transcripts
- Our proposed approaches achieve more than 7% relative improvement compared to the baseline

# Thanks for your attention! ☺
# Q & A